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ZOBIA ILYAS

FREQUENCY DOMAIN CORRELATION BASED COMPRESSED SPECTRUM SENSING FOR COGNITIVE RADIO

Master of Science Thesis

Examiners: Prof. Markku Renfors and Dr. Tech. Sener Dikmese.
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ABSTRACT

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As wireless applications are growing rapidly in the modern world, this results in the shortage of radio spectrum due to the fixed allocation of spectrum by governmental agencies for different wireless technologies. This problem raises interest to utilize spectrum in a more efficient way, in order to provide spectrum access to other users when they need it. In wireless communications systems, cognitive radio (CR) is getting much attention due to its capability to combat with this scarcity problem. A CR senses the available spectrum band to check the activity of primary users (PU). It utilizes the unused spectral resources by providing access to secondary users (SU). Spectrum sensing (SS) is one of the most critical issues in cognitive radio, and there are various SS methods for the detection of PU signals. An energy detector (ED) based SS is the most common sensing method due to its simple implementation and low computational complexity. This method works well in ideal scenarios but its detection performance for PU signal degrades drastically under low SNR values in the presence of noise uncertainty. Eigenvalue-based SS method performs well with such real-life issues, but it has very high computational complexity. This raises a demand for such a detector which has less computational complexity and can perform well in practical wireless multipath channels as well as under noise uncertainty.

This study focuses on a novel variant of autocorrelation detector operating in the frequency domain (FD-AC). The method is applicable to PUs using the OFDM waveform with the cyclic prefix (CP). The FD-AC method utilizes fast Fourier transform (FFT) and detects an active PU through the CP-induced correlation peak estimated from the FFT-domain samples. It detects the spectral holes in the available electromagnetic spectrum resources in an efficient way, in order to provide opportunistic access to SUs. The proposed method is also insensitive to the practical wireless channel effects. Hence, it works well in frequency selective channels. It also has the capability to mitigate the effects of noise uncertainty and therefore, it is robust to noise uncertainty. FD-AC facilitates partial band sensing which can be considered as a compressed spectrum sensing method. This allows sensing weak PU signals which are partly overlapped by other strong

PU or CR transmissions. On the other hand, it helps in the reduction of computational complexity while sensing PU signal in the available spectrum band, depending on the targeted sensitivity. Moreover, it has highly increased flexibility and it is capable of facilitating robust wideband multi-mode sensing with low complexity. Its performance for the detection of PU signal does not depend on the known time lag, therefore, it can perform well in such conditions where the detailed OFDM signal characteristics are not known.

PREFACE

This Master of Science thesis is written at the Department of Electronics and Communications Engineering, Tampere University of Technology, Finland.

First of all, I would like to express my deepest gratitude and respect to my supervisor, Prof. Markku Renfors for not only introducing me to this research topic but also for his kind attitude, support during this thesis work, his enthusiastic guidance and listening to the problems within the process. It could not have been done without his supervision, advice and attention towards my work.

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I am really thankful to my parents and family for their love, kindness, good wishes, continuous support, and immense prayers to make this thesis work possible. Whatever I have achieved is because of them.

Finally, I would like to express my heart-felt thanks to my friends in Pakistan and Finland, Shameen Khurram, Rakhshanda Imtiaz, Anum Zahra, Md Shohidur Rahman and especially Hasan Iftikhar for their vital encouragement, untiring assistance, moral support, love and caring attitude during my thesis work.

I would like to dedicate this thesis work to my parents.

Tampere, 15.02.2016

Zobia Ilyas

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LIST OF ABBREVIATIONS

AuF	Autocorrelation function
AWGN	Additive white Gaussian noise
CAF	Cyclic autocorrelation function
CC	Cognitive controller
CCC	Common control channel
CF	Cyclic frequency
CLT	Central limit theorem
CP	Cyclic prefix
CR	Cognitive radio
CSD	Cyclic spectral density
CSI	Channel-state information
CSS	Compressed spectrum sensing
DFT	Discrete Fourier transform
DOSA	Dynamic and opportunistic spectrum access
ED	Energy detector
ERFC	Complementary error function
FCC	Federal Communications Commission
FD-AC	Frequency domain autocorrelation
FFT	Fast Fourier transform
FT	Fourier transform
IFFT	Inverse fast Fourier transform
ITU	International Telecommunication Union
LLRT	Log-likelihood ratio test
NP	Neyman-Pearson
OFDM	Orthogonal frequency division multiplexing
PU	Primary user
RF	Radio frequency
ROC	Receiver operating characteristic
SNR	Signal to noise ratio
SS	Spectrum sensing
SU	Secondary user

LIST OF SYMBOLS

H_0	Hypothesis 0 in NP test
H_1	Hypothesis 1 in NP test
H_k	Complex gain of subband K
K	FFT size in FD-AC sensing
K_{comp}	Number of FFT subbands used in compressed sensing
k_0	SNR scaling
M	Number of FFTs averaged for correlation
m_Δ	Subcarrier sample offset
N	Observation length
N_c	Length of cyclic prefix
$\mathcal{N}_c(.)$	Complex Gaussian distribution of signal
N_d	OFDM symbol duration
$\mathcal{N}_R(.)$	Gaussian distribution for real valued numbers
N_s	CP-OFDM symbol duration
P_D	Detection probability
P_{FA}	False alarm probability
P_M	Probability of miss-detection
$Q(.)$	Gaussian Q-function
$Q^{-1}(.)$	Inverse Gaussian Q-function
$R(\tau)$	Autocorrelation function of the received signal
RX	Receiver
$R_y^\alpha(\tau)$	Cyclic autocorrelation function
$S(f,a)$	Cyclic spectral density
$s[n]$	Transmitted OFDM signal
T_c	Time interval for cyclic prefix
T_u	Time interval for useful data
TX	Transmitter
T_ρ	Test-statistics
$w[n]$	AWGN samples
$x[n]$	Received PU signal with channel effects
$y[n]$	Received signal by cognitive user
σ_s^2	Variance of signal
σ_n^2	Variance of noise
λ_ρ	Experimental threshold
τ	Time lag

μ	Autocorrelation coefficient
α	Cyclic frequency
$y_{k,m}$	Output of FFT blocks
Ω	Set of used subcarriers

1. INTRODUCTION

1.1 Thesis work motivation and background

With the increasing demand in higher data transmission rates, capacity, mobility and security, development of efficient wireless network technologies has been considered as a central matter of attention. But as the number of users and multimedia applications are increasing rapidly, the availability of radio spectrum in modern wireless technologies has become a crucial issue [51].

In the past few years, assignment of fixed radio spectrum was providing a safe and effective way for communication without interference between users. But, as wireless applications are growing rapidly, there is a shortage of radio spectrum availability for modern wireless technologies [69, 73]. In order to overcome the radio spectrum shortage, many researches have been done to manage the available radio spectrum in a much better way. Even though the available spectrum has already been assigned by governmental agencies to different licensed users for different purposes for a long time; the studies revealed that the allocated spectrum is sometimes not being used at all or it can also be sparsely used. This is illustrated in Figure 1.1 [7, 69, 22, 75], which shows clearly the usage of the spectrum in recent studies done by authorities. It can be seen from the figure that some bands of the radio spectrum are densely used by subscribers, whereas much of the spectrum is vacant and some portion of spectrum is being partially used [7, 12, 43, 45, 61].

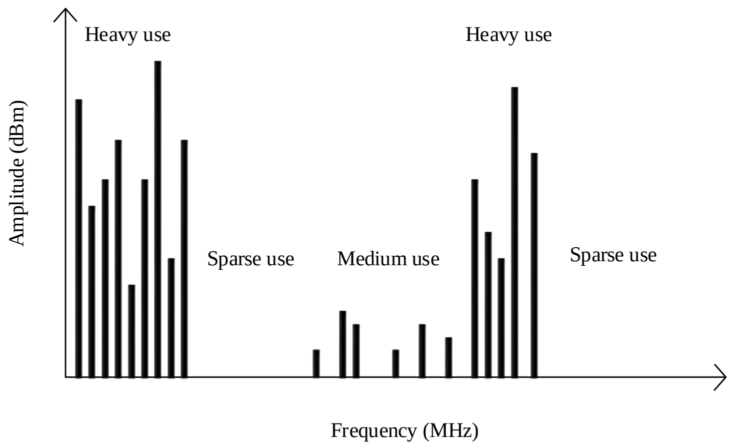

Figure 1.1. *Utilization of spectrum.*

A study of spectrum utilization has also been made by the US Federal Communications Commission (FCC) [7, 49, 65]. According to them, the usage of assigned licensed spectrum by the PUs differs from 15% to 85% and it also includes significant time and space variation. According to these studies, it has been concluded that the insufficiency of available spectrum is not actually due to the physical limitations, but the main reason is that the assignment of fixed spectrum by FCC and International Telecommunication Union (ITU) to different licensed PU's is not an efficient way. After this study, it helps in the progress of wireless communication networks in its exponential growth if the CR approach is applied to opportunistically share the radio spectrum when it is not being used by the PUs.

To combat with the scarcity problem, cognitive radio (CR) has got more attention in the recent years [49]. CR devices sense the spectrum, which is called spectrum sensing (SS). After sensing, CR identifies the accessibility of spectrum in time as well as in the frequency domain, by checking the presence or absence of on-going transmissions in the band. After checking the availability of some portion of the spectrum, the CR selects the best available channel and then shares it with other users, which is called spectrum sharing by unlicensed secondary users (SUs). Based on the identification process, the CR makes a decision, i.e., if the PU signal is not active, the corresponding SU starts its transmission, otherwise it remains silent. Hence, the CR user applies dynamic and opportunistic access of the radio spectrum (DOSA). In the meanwhile, it also guards PUs from harmful interferences by vacating the channel after detecting a re-appearing PU by sensing the spectrum (spectrum mobility) [6, 13, 24, 40, 55, 60]. CR enhances the spectrum efficiency by combining spectrum sensing and sharing of spectrum with each other [6]. The CR users can identify and contact each other through a common medium which is called common control channel (CCC). CCC helps in identification of vacant spectrum to make these frequencies useful for SUs [3, 5]. But, in order to make a communication link possible for two CR nodes, they must meet on the same channel.

Spectrum sensing is a tool which is used by a CR to find a suitable spectral hole in its desired frequency band in order to exploit it for the required throughput and quality of service (QoS) [69]. Hence, it helps to improve the utilization of spectrum in an efficient way and it also reduces harmful interference to the authorized users in a geographical area. It is considered as one of the most critical parts in CR networks [65], and various alternative sensing methods are available in the literature.

The main focus of this thesis is to investigate SS methods based on frequency domain autocorrelation (FD-AC). The method is applicable to PUs which utilize the orthogonal frequency division multiplexing (OFDM) waveform with the cyclic prefix (CP). When the OFDM signal parameters are known, the sensing is based on detecting the correlation peak at the known time lag corresponding to the useful OFDM symbol duration. In case of unknown OFDM signal parameters, the maximum value of the correlation is detected to check the presence or absence of the PU signal. Even though the method is limited to

OFDM primaries, it has wide applicability since CP-OFDM is widely deployed in current broadband wireless communication systems, including digital audio broadcasting (DAB), terrestrial digital video broadcasting (DVB-T), 3GPP LTE, Wi-Fi, wireless LAN (WLAN) radio interfaces IEEE 802.11 a, g, etc. and many other wireless systems.

In some sensing techniques, some knowledge of PU's waveform and parameters is required, but in some other techniques (the so-called blind methods), no information about the PU signal is assumed. Among different SS algorithms which require minimal information about the PU, energy detector (ED) is the most popular one. The main reason for its wide fame is its simplicity and very low computational complexity. ED will be briefly explained in Section 2.2. But performance analysis of this detector shows that it is not a good solution for sensing PU signal under very low signal to noise ratio (SNR) and noise uncertainty (NU) challenges. But these cases need to be handled because in real-life, receiver non-idealities and multipath propagation occur which badly degrade the performance of spectrum sensing. In multipath propagation, the receiver gets a signal not only from the direct line-of-sight path from the transmitter, but also from many other different paths which may exist, e.g., due to reflections occur in the physical environment. Figure 1.2 shows the presence of such multipath propagation, together with shadow fading due to obstacles, which causes the SNR of the received signal to become very small, lowering the detection performance [2, 12, 36, 50, 62].

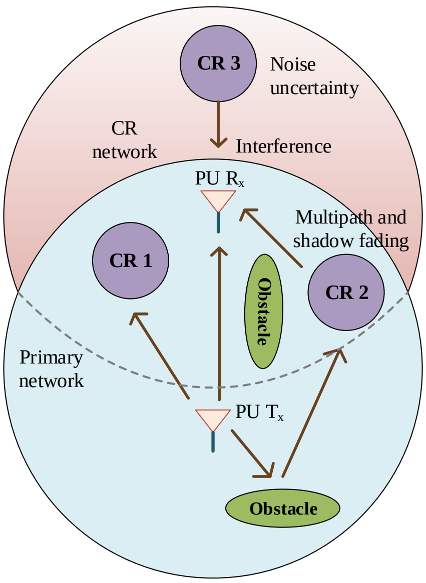

Figure 1.2. *Multipath and shadow fading, noise uncertainty and interference in cognitive radio network (CRN).*

This problem motivates to design a detector which can resolve such issues. For this purpose, autocorrelation based advanced SS method will be used in this study. Autocorrelation method is implemented effectively in the frequency domain through fast Fourier transform (FFT) processing in order to sense the spectrum in CR networks. Compressed spectrum sensing (CSS) element is used in the FFT-domain autocorrelation processing in order to make it computationally more efficient. The performance results from FD-AC based method are compared with ED to find out pros and cons of both detectors.

Advantages of using FD-AC based detector over ED are following: Whether pre-known information about PUs is present or not, it can work efficiently in both cases. It is robust to NU, unlike ED, because ED performance for detecting PU signal degrades drastically in presence of NU. It also works well in the presence of frequency selective channels. Another benefit of using this detector is that it also facilitates a partial band (i.e., compressed) sensing in the frequency domain. This helps in the minimization of computational complexity by using just a sufficient amount of data for each specific sensing task. CP-OFDM is used as the PU waveform. In OFDM signals, CP introduces periodicity, which can be detected by the autocorrelation method.

In order to find which SS technique is robust to NU at low SNR values and under selective channel cases, simulations and results validation is carried out by using MATLAB.

There are two factors which determine the detection performance. One is probability of detection (P_D) and the other is the probability of false alarm (P_{FA}). P_D is the probability of correctly detecting the presence of an on-going PU transmission. P_{FA}, in turn, is the probability that a PU is falsely detected to be active, while there is only noise present in the channel. This type of false detection of a signal reduces efficiency of secondary spectrum use, while low P_D causes interference to the authorized primary users [77]. Commonly, the target P_{FA} (e.g., 0.1 or 0.01) is a fixed parameter for the sensing receiver. A Neyman-Pearson (NP) test is used formulate the detection problem. It comprises two hypotheses: hypothesis 0 $\left(H_0\right)$ and hypothesis 1 $\left(H_1\right)$ [61]. NP test is defined as:

$$\begin{aligned} H_0 &: y[n] = w[n] \\ H_1 &: y[n] = \overbrace{s[n] \otimes h[n]}^{x(n)} + w[n] \end{aligned} \tag{1.1}$$

Here, $y[n]$ is the received signal by cognitive user, $s[n]$ is a transmitted signal by PU, $w[n]$ is additive white Gaussian noise (AWGN), $h[n]$ is channel and $x[n]$ is received PU signal with channel effects.

1.2 Objectives of the thesis

The main objective of this thesis is to test the performance of the autocorrelation based detector realized in the frequency domain using FFT processing in challenging spectrum sensing scenarios, with both known and unknown CP-OFDM signal characteristics, with known and unknown time lags accordingly. Many researchers use flat fading and AWGN cases for SS performance analysis, but the detectors might fail in real scenarios, in the presence of NU, frequency selective channels, and shadow fading. FD-AC detector works fairly well under such conditions even with very low SNR values. Also compressed spectrum sensing ideas are studied in the FD-AC context. The reason for using CSS element in this study is that it provides a possibility for reduced computational complexity in sensing, depending on the requirements of the sensing scenario.

1.3 Outline of the thesis

In order to achieve the objectives of this thesis, this study covers development of a novel FFT-domain AC based sensing method with CSS elements, its reliable simulation based performance analysis under NU and low SNR cases, as well as computational complexity analysis. The outline of the thesis is as follows:

- Chapter 2 introduces the central concepts of CR, its physical architecture, functionality, features, and basic cognitive tasks. It also includes an introduction to spectrum sensing and common sensing algorithms.
- Chapter 3 focuses on FD-AC based method and an addition of CSS element in this detector. It also briefly explains the signal model used in this study, which is CP-OFDM.
- Chapter 4 is related to the system model of techniques that are used in this study and it also provides a description of the simulation environment.
- In Chapter 5, comparison between different techniques is made based on simulation results.
- Chapter 6 gives concluding remarks about the whole study.

2. COGINITIVE RADIO AND SPECTRUM SENSING ALGORITHMS

As the electromagnetic radio spectrum has already been assigned to PUs by regulators, a vital problem of scarcity of radio spectrum arises in past years due to the increase of usage of multimedia applications which need higher data rates. A report was prepared by the spectrum-policy task force, according to which they are trying to solve this issue because the shortage of available spectrum is a vital subject for the development of further wireless communication technologies. FCC has assigned the spectrum to PUs which are rigid and have a long term allocation approach of spectrum. According to FCC, some frequency bands are highly occupied by PUs, some are partially occupied and almost 70 percent of spectrum are not being used in the United States. Availability of spectrum varies in the time domain from milliseconds to hours. Due to this uneven distribution of radio spectrum to PUs, there is a need to use unoccupied spectrum in an efficient way by giving spectrum access to SUs when PUs are not active. This arouses the concept of reuse of frequency bands by sensing the spectrum if it is occupied by PUs or ready to use by SUs. In order to sense the availability of spectrum, concept of CR has been introduced [45, 55, 77].

This thesis is using the same idea to improve the access of electromagnetic radio spectrum by unlicensed wireless applications to enhance wireless technologies.

2.1 Basics of cognitive radio

CR is an appealing solution to the spectrum congestion problem, as it provides opportunistic access of frequency bands which are idle at some time slot and available to use by other unlicensed applications. So CR focuses on providing dynamic spectrum access instead of the fixed allocation of frequency bands to various wireless applications and hence it makes better utilization of radio spectrum. According to FCC, CR is defined as: “CR: A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets” [7, 55, 65, 77].

Physical architecture of a CR transceiver and RF front-end unit are shown in Figure 2.1 and Figure 2.2, respectively [6, 7, 11, 12].

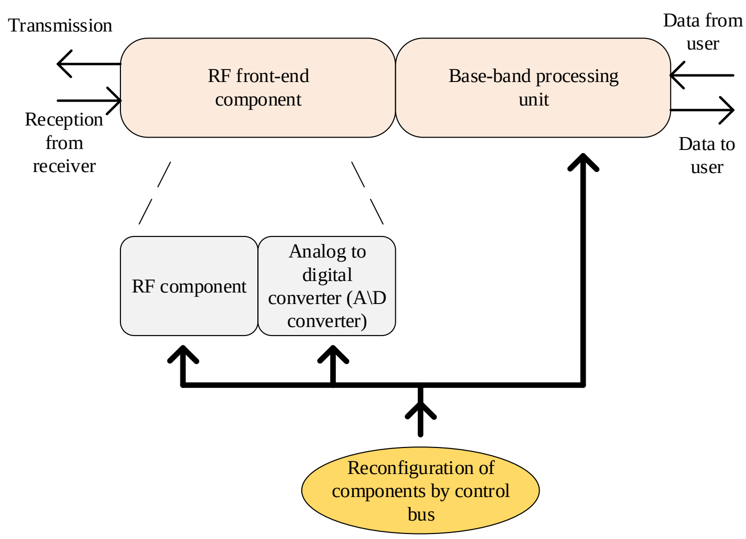

***Figure 2.1.** A CR transceiver in physical architecture of CR.*

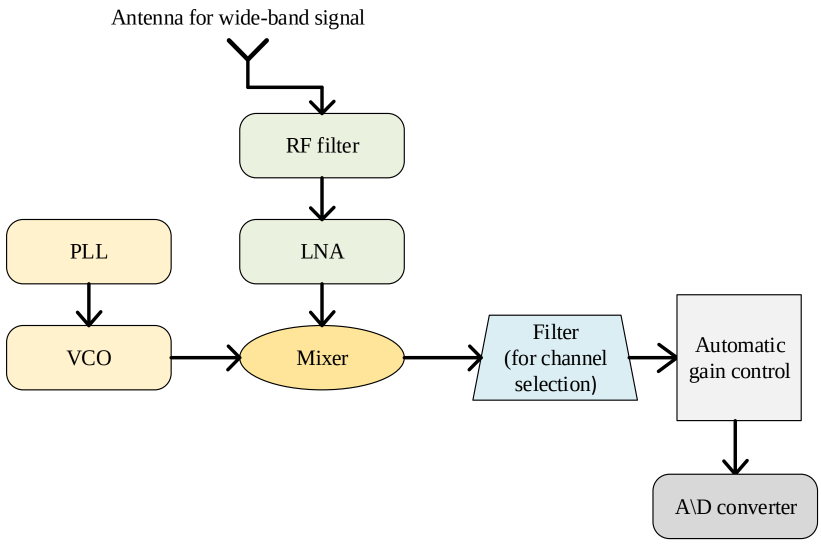

***Figure 2.2.** Front-end view of wide-band analog signal in physical receiver architecture of CR.*

The physical architecture of CR transceiver consists of RF front-end unit and a base band processing unit. Reconfiguration of components is done by using a control bus which enables it to adapt to the RF environment. In a baseband processing unit, a signal is sent for modulation/ demodulation and for encoding and decoding. In the RF front-end unit, a received signal is filtered, amplified and then mixes with RF frequency and translates the signal to baseband or intermediate frequency (IF). This process is done by using a voltage control oscillator (VCO). A phase locked loop (PLL) is also used to lock the signal at a particular frequency. After this, the signal is passed through a channel selection filter which selects the preferable channel while rejects others. Then, the signal is sent to an automatic gain control unit, which is used to control the amplitude of the received signal even when there are many variations in the amplitude of the transmitted signal. The signal is then sampled by using analog to digital (A/D) converter. A signal with weak power has very less detection probability. Hence, it gets difficult to detect such PU signals from electromagnetic frequency bands by using physical architecture of CR. Therefore, it becomes a problematic issue for next generation networks.

According to CR functionality, CR is defined as [45, 54, 55, 60]: CR is an intelligent wireless communication system that is aware of its surrounding environment (i.e., the outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:

1. Highly reliable communications whenever and wherever needed.
2. Efficient utilization of the radio spectrum.

According to above definition, there are three basic cognitive tasks as shown in Figure 2.3 [7, 45, 58, 59, 60].

1) Radio-scene analysis is done by CR which is used to estimate the interference temperature of radio environment and it also detects the unoccupied frequency bands (known as spectrum holes). When electromagnetic spectrum is not utilized by devices in an effective way, some empty holes in frequency bands are left and these are known as spectrum holes. These spectrum holes can be defined as: *A frequency band which has been allocated to PU signal, but PU signal leaves it unused for certain time and particular geographic location.*
2) Channel identification which is used to estimate channel-state information (CSI) and it also calculates the required channel capacity by a transmitter.
3) Transmit-power control and dynamic spectrum management.

Tasks 1 and 2 are done in the receiver side however task 3 is done by CR at the transmitter side.

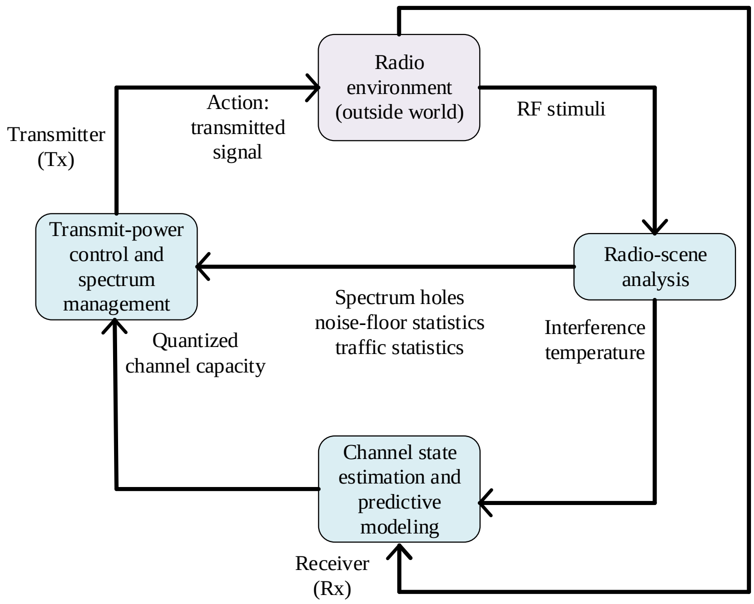

Figure 2.3. *Fundamental cognitive tasks.*

Besides basic cognitive tasks, CR devices have four main functions which can be seen in Figure 2.4 [7, 45, 51, 54, 55, 60].

- Spectrum sensing: CR senses the radio frequency bands, captures their information and then detects if there is any spectral hole or not in a certain time and geographical area.
- Spectrum analysis: It analyzes the features and properties of spectral holes that are already detected by SS.
- Spectrum decision: A decision is made whether a user can occupy the specific spectrum band or not. Then after making decision, CR provides appropriate spectrum holes for unlicensed SUs. This decision is made according to user requirements and features of radio bands.
- Spectrum mobility: After selecting appropriate spectrum, CR allows users to perform communication over a specific band. However, CR should keep checking radio environment as it changes with time, frequency and space. CR transfers the transmission by using spectrum mobility function when a spectrum band utilizing by user becomes unavailable by the arrival of a PU.

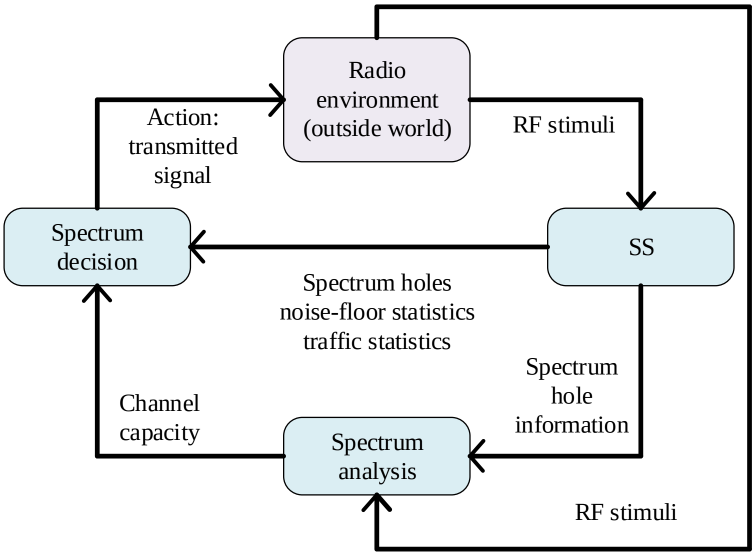

Figure 2.4. *Functionality CR devices.*

Three most important features of CR are as follows [71]:

1) Sensing: CR should be clever enough to sense the electromagnetic spectrum and should detect the spectrum band where PU signal is absent.
2) Flexibility: CR should be able to provide SU the access of a spectrum band which is vacant and not being used by PU signal, by translating signal frequency to adjust it into a spectrum segment which is not being used by PU. CR should also be capable enough to change shape of spectrum in order to use the frequency band in efficient manner.
3) Non-interfering: CR should also keep notice not to cause harmful interference to PU signal when it is providing spectrum access to SUs.

SS in CR devices is the most critical part in CR functionalities as it contains the operation to detect the spectral holes in spectrum. This thesis is focused on SS part in CR.

2.2 Spectrum sensing techniques

As SS is the most important part in CR networks, several SS techniques have been proposed in the literature. These techniques are suggested according to different scenarios, and they have different properties in terms of sensing performance and implementation complexity. These are based on detection of spectral holes in available spectrum in time, frequency and space. CR detects spectral holes and allows SUs to use them until the presence of PU [36]. The concept of a spectrum hole has been illustrated in Figure 2.5 [7, 51, 77].

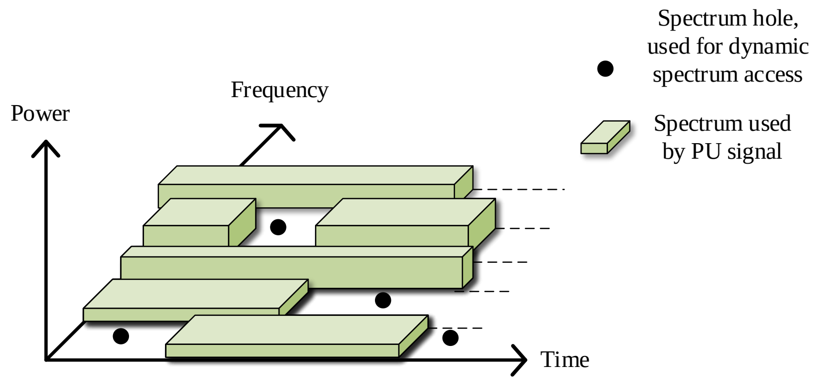

Figure 2.5. *Concept of spectrum hole.*

These spectral holes can be occupied by SUs after sensing by CR and classified into two categories:

1. Temporal spectrum holes.
2. Spatial spectrum holes.

These holes are illustrated in Figure 2.6.a and 2.6.b. Temporal spectral hole is free from PUs while sensing the band by CR in time domain and can be utilized by CR users in a provided time slot. Due to time domain operation and the presence of SUs inside coverage area of PU transmission, CR only needs to identify the presence or absence of PU. Therefore, a temporal spectral hole does not need complex signal processing. In a spatial spectral hole, the required spectrum band is not available due to PU transmission. However, this transmission is only in a restricted area, so CR provides the band for SU well outside this area. As SUs occupy these holes outside the coverage of PU's transmission and there is no PU receiver outside the coverage area of PU transmission, so CR requires complex signal processing to avoid interference with a PU signal [19, 56].

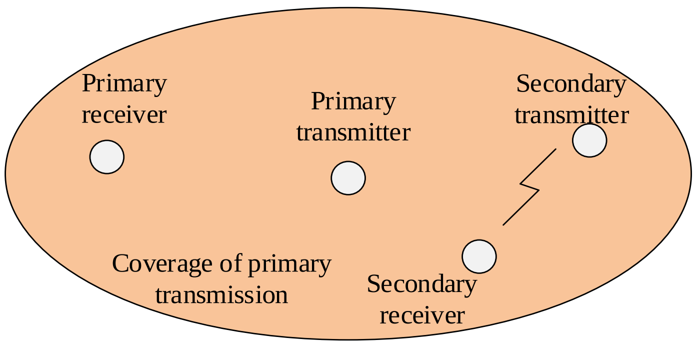

Figure 2.6.a. *Temporal spectrum holes for secondary communication.*

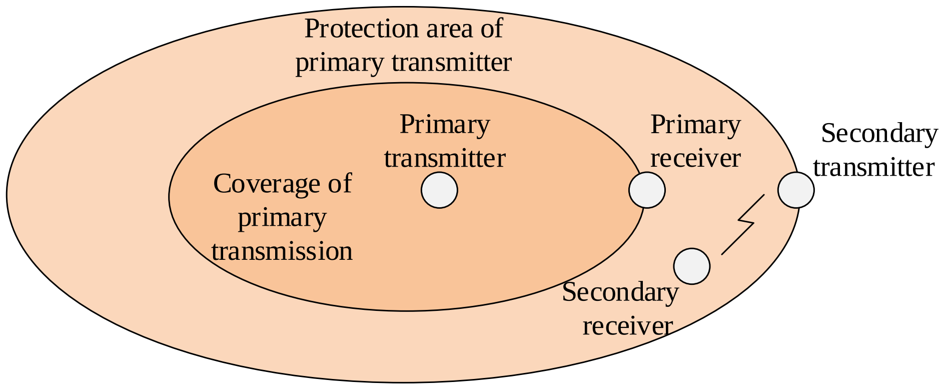

Figure 2.6.b. *Spatial spectrum holes for secondary communication.*

Depending upon the amount of spectrum occupation of the incoming RF stimuli, radio frequency bands can be classified into three types [19, 45, 51, 67] as follows:

1. White spaces, which are vacant and have only AWGN and can be used by CR users.
2. Grey spaces are partially occupied bands with low power PUs.
3. Black spaces, where high power PUs are present, at least some of the time. Hence, these are not allowed to be used by SUs as they would cause much interference to the local users.

After sensing spectral holes, the CR system provides white spaces (for sure) and grey spaces (to some extent) to unlicensed wireless applications to use them. However, as these holes change with time, these are continuously sensed by the CRs.

SS techniques focus on low implementation complexity and good accuracy of sensing spectrum holes and to provide SUs a spectrum without interference to PUs. In a real scenarios, the performance of detection of PUs should be accurate even under very low SNR cases. The spectrum sensing methods are of three types: Total blind SS, semi-blind SS, and non-blind SS [73].

- Total blind SS does not need any prior information about a PU signal and noise.
- In semi-blind method, the information of noise variance (power) is important to be known.
- Non-blind methods need some prior information about the PU signal.

Classification of SS techniques based on signal detection approach is shown in Figure 2.7 [2, 23, 50]. According to it, sensing techniques can be classified into two main categories: coherent detection and non-coherent detection. Detecting the signal can also be classified according to its bandwidth scenario (narrow-band and wide-band) as shown in Figure 2.7.

- Coherent detection needs some prior information about the PU signal for detecting it. Using this knowledge, signal after reception is compared with the prior knowledge of PU signal. Matched filter detection and cyclo-stationary feature detection depend on this principle.

- Non-coherent detection does not need any prior information about the PU signal to detect it. ED and wavelet based detection are based on the non-coherent principle.
- ED can be utilized in the narrow band as well as in the wide band sensing context.
- CSS methods are commonly wide band sensing approaches.

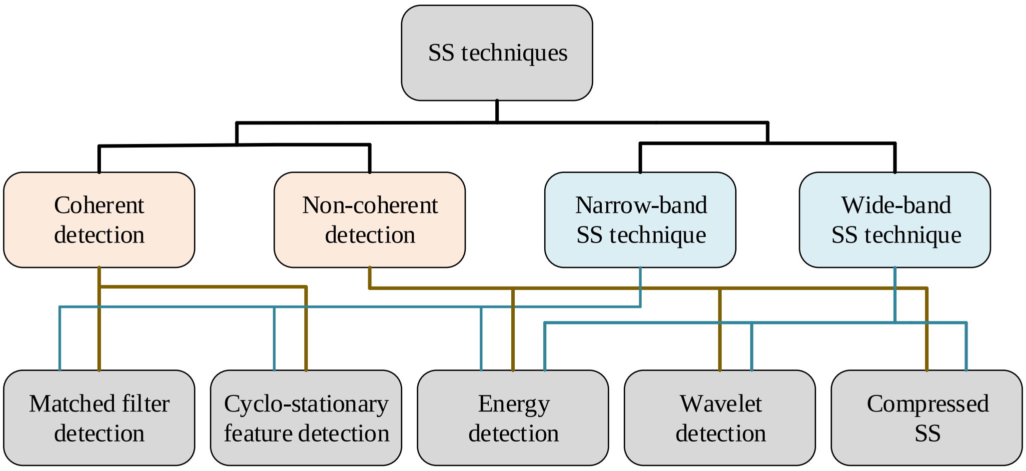

Figure 2.7. *Classification of SS techniques.*

Another classification of SS techniques is shown in Figure 2.8 [73].

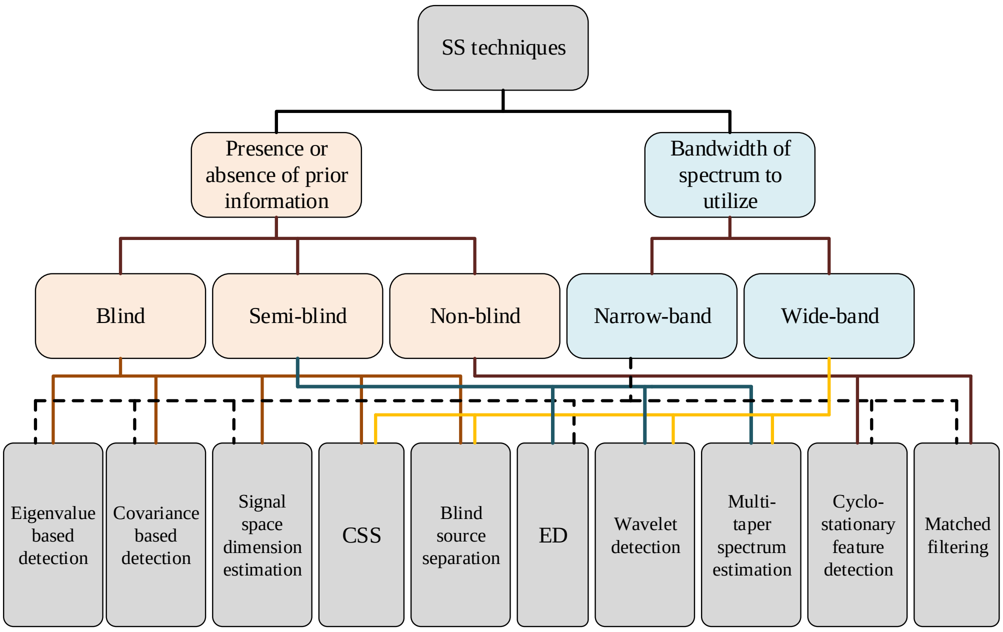

Figure 2.8. *Classification of SS techniques.*

Some selected SS techniques are briefly explained below.

Energy detector

Among all SS techniques, ED is the most common method for SS due to its low computational complexity. ED evaluates the noise variance to set its threshold value and it does not need prior information of the PU signals. Hence, it is considered as semi-blind sensing method. It is an optimal technique as it also detects primary transmissions even when CR does not know the features of the PU signal [27, 73]. But its main drawback is that ED needs to choose a certain threshold value to detect the PU signal, so this is how they become non-robust because the threshold value completely depends on the noise variance. These detectors are not able to discriminate interference from the PU signal and AWGN, and this is the reason why these detectors are not reliable in the presence noise uncertainty. It is not able for detecting spread spectrum signals [1, 2, 26, 39, 50, 51, 54, 55, 56, 77, 80].

Eigenvalue sensing method

While using an ED, noise uncertainty becomes a crucial issue. This problem is solved by introducing an eigenvalue based detector which does not need noise variance information. It uses eigenvalue of the covariance matrix of signals which are received at SUs. Two methods for this detector have been proposed, one is the ratio of maximum eigenvalue to minimum eigenvalue while other method is based on the ratio of average eigenvalue to minimum eigenvalue. This detector performs well even if it does not know features of a PU signal and channel. A vital shortcoming of this detector is that it has very high computational complexity [25, 31, 38, 54, 78, 79].

Waveform based sensing

This type of sensing determines the correlation with familiar patterns of signal such as preambles, pilot patterns and spreading sequences. It is highly sensitive towards synchronization errors. If there are strong correlations in the PU signal structure, this sensing method can be more reliable and robust than an ED. In this sensing method, knowledge the PU signal patterns becomes a vital issue. It is non-blind SS method [50, 51, 54, 56, 70, 77].

Cyclostationary feature based spectrum sensing method

As a modulated signal has periodicity due to CP, sine wave carriers or by many other ways, this results in building cyclostationary features in such signals due to periodicity or due to its statistics (mean and autocorrelation). Such detectors exploit the cyclostationarity features of a received signal to detect PU signal. It is non-blind SS method. Noise is wide sense stationary (WSS) and has no correlation while modulated signals have periodicity and thus they have cyclostationarity property and there exist correlations between signals. Based on this reason, it can easily distinguish noise from a PU signal unlike the ED. Hence, this detector has better detection performance than ED, and is robust against noise uncertainty and it has capability to reject the interface between two adjacent channels. It is an efficient detector but it has a very high computational complexity and requires a lot of time for observation. It also requires a very large number of samples to utilize the cyclostationarity of the signal.

The cyclic spectral density (CSD) function of received signal can be obtained from discrete Fourier transform (DFT) of cyclic autocorrelation function (CAF) which is given by [42]:

$$S(f,a)=\sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau)e^{-j2\pi f\tau} \tag{2.1}$$

where $S(f,a)$ is known as CSD and CAF is given by:

$$R_y^{\alpha}(\tau)=E\left[y(n+\tau)y^{*}(n-\tau)e^{j2\pi\alpha n}\right] \tag{2.2}$$

where $R_y^{\alpha}(\tau)$ function is CAF and α is cyclic frequency (CF). CSD gives peak values when CF becomes equal to fundamental frequencies of a transmitted signal $x(n)$. This detector detects a PU signal by looking for the unique CF corresponding to a peak in CSD plane. Moreover, they are very sensitive to CF mismatch [1, 2, 50, 51, 54, 56, 77].

Compressed spectrum sensing

CSS is a novel sensing model which goes against a common approach of data acquisition. By adding this element in the sensing method, it does not need all the number of samples to detect a PU signal, instead one can recover certain signals by using very few samples or measurements. Hence, it is also known as compressed sampling [2, 23, 50]. This thesis uses CSS element during sensing methodology. Detail of this paradigm is illustrated in Chapter 3.

3. AUTOCORRLEATION BASED DETECTION IN FREQUENCY DOMAIN USING FFT PROCESSING

This chapter discusses an efficient subband based autocorrelation (AC) detector for SS. AC is basically a time-domain method, but it can be implemented also through frequency domain processing. ED under noise variance uncertainty and frequency selective channel is also investigated and used as a reference in the performance evaluation of the proposed FD-AC based detector. A CSS element is also considered in the FD-AC based detector to reduce computational complexity. The FD-AC detector is introduced in the context of wideband spectrum sensing using a fast Fourier transform (FFT) based spectrum. FFT and inverse FFT (IFFT) are applied to calculate the autocorrelation function (AuF) of the received signal effectively in frequency domain. For this purpose, FFT and IFFT concepts are important to consider in this study, so we start this chapter by introducing these techniques.

3.1 FFT and IFFT analysis

This section briefly describes the concepts of FFT and IFFT which are used in the FD-AC sensing process, in order to detect a PU signal in electromagnetic spectrum.

Basically, the main function of a Fourier transform is to transform the time domain signal into a frequency domain representation in the signal processing context. Transforming a signal from the frequency domain back to the time domain is called inverse Fourier transform (IFT). As Fourier transform becomes a bridge between time domain and frequency domain signals, it serves well to go back and forth between waveform and spectrum with open the doors for the development of many technologies and novel applications [30].

To define FFT, it is important to know the concept of continuous-time Fourier transform [8]. FT converts a signal from a time domain representation to the frequency domain. FT and inverse FT are mathematical operations which are defined as follows:

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-i2\pi ft} dt \tag{3.1}$$

$$x(t) = \int_{-\infty}^{\infty} X(f) e^{i2\pi ft} df \tag{3.2}$$

where $X(f)$ is frequency domain function and $x(t)$ is time domain function. In this mathematical equation, frequency goes from $-\infty < f < \infty$ and time from $-\infty < t < \infty$ and $i = \sqrt{-1}$.

For sampled versions, DFT and IDFT are defined as follows:

$$X(n) = \frac{1}{N}\sum_{k=0}^{N-1} x(k) e^{-i2\pi nk/N} \tag{3.3}$$

$$x(k) = \sum_{k=0}^{N-1} X(n) e^{i2\pi nk/N} \tag{3.4}$$

where $n = 0,1,...,N-1$ and $k = 0,1,...,N-1$. In the above equations, $X(n)$ and $x(k)$ both are generally complex functions.

When expression $e^{i2\pi/N}$ is replaced by term W_N, then DFT can be written as follows:

$$X(n) = \frac{1}{N}\sum_{k=0}^{N-1} x(k) W_N^{-jk} \tag{3.5}$$

$$x(k) = \sum_{j=0}^{N-1} X(n) W_N^{+jk} \tag{3.6}$$

There are many ways to compute a DFT, but for transform length which are powers of 2, the most efficient way to compute a DFT is by using the FFT algorithm. Taking inverse of FFT is called an IFFT. FFT considers as working efficiently because it minimizes the number of arithmetic operations (additions and multiplications) involved in calculating the transform [20, 74].

The reduction in the number of multiplications for DFT calculation by using the FFT process instead of a direct method is shown by Table 3-1. A FFT process not only reduces the number of multiplications, but it also reduces the round-off errors that are accompanying these computations by the factor of $(\log_2 N)/N$, where N is the transform length [20, 37, 52].

Table 3-1. *DFT calculation: A comparison between methods used to compute DFT.*

Process	Mathematical equation	Number of multiplications using approximation (upper bounds of comparison)	
		Direct method	Using FFT process
DFT	$\sum_{k=0}^{N-1} x(k) e^{-2\pi jrk/N}$ $r = 1, 2, \ldots, N-1$	N^2	$2N \log_2 N$

Some important application of FFT are as follows:

1. Computing a spectrogram, which can be defined as a short term power spectrum of a signal.
2. Efficient implementation of digital filtering, i.e., convolution two discrete-time sequences.
3. Correlation between two discrete-time signals.

Digital filtering and correlation operations can also be done in time domain without using FFT, but as FFT is computationally very efficient, FFT based implementation becomes in many cases more efficient in terms of multiplication rate, so this increases the interest to use FFT. Figure 3.1 shows a comparison between the number of operations that are required to compute a DFT using FFT and without using FFT, i.e., by using direct method. Again N is the number of samples in the time-domain sequence, and in the transform as well [8, 30, 32, 37].

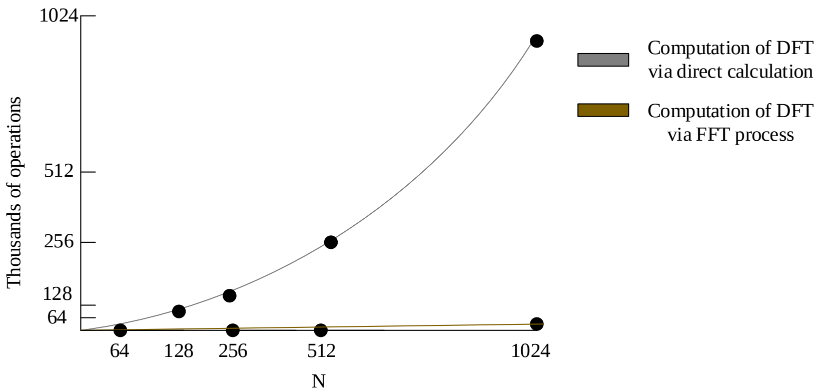

Figure 3.1. *Requirement of number of operations for DFT computation by FFT algorithm vs. requirement of number of operations for DFT computation by direct calculation.*

By observing the mathematical computation of DFT and IDFT, it can be concluded that IFFT can be implemented by similar and equally efficient algorithms as FFT [18].

3.2 Autocorrelation function performed over CP-OFDM based PU signals in CRN system

OFDM is quite popular and dominating modulation technology which is being used in many applications of wireless communication systems. In this thesis, PU is assumed to use OFDM signal, considering both cases with and without knowledge of the signal characteristics. Autocorrelation method is applied to OFDM signal due to the presence of the CP, which can be effectively utilized in SS.

Basics of OFDM are essential for understanding the later developments and they are presented briefly in this section. OFDM has very high spectrum efficiency and it is resistant to multipath fading through its robust and effective channel equalization scheme [9, 29, 53]. Hence, this technique has proven to be very reliable for wideband transmission systems, such as terrestrial mobile communication, digital terrestrial TV broadcasting, wireless LAN and many more [21, 35].

As OFDM is widely used in wireless communication systems, PUs in CRs commonly use OFDM transmission. An essential feature of OFDM systems is to use CP, which is inserted at the transmitter side. Thus, OFDM possesses a strong explicit correlation structure [4, 47].

OFDM is a multicarrier transmission technique generated through IFFT processing at the transmitter side [53, 66]. The CP structure reduces chance of inter symbol interference (ISI) between consecutive OFDM symbols and it also preserves the orthogonality of the subcarriers with multipath channels if the CP is at least as long as the channel delay spread[41]. The OFDM symbol is derived from the IFFT of the sequence of N_d complex subcarrier symbols, some of which may be zero, corresponding to guard bands. As illustrated in Figure 3.2, CP consists of the last N_c samples of the OFDM symbol (of length N_d samples) and it is added as a preamble to the useful OFDM symbol to get the total OFDM symbol length of $N_c + N_d$ sample [4, 46, 47, 63].

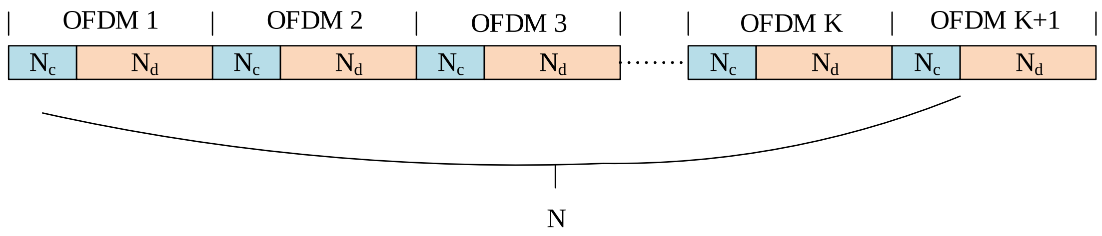

Figure 3.2. *Model for CP- OFDM signal. N samples, as illustrated, are used in the FD-AC algorithm for SS.*

The main aim of the CP is to provide the orthogonality of the modulation symbols at the receiver by converting the Toeplitz convolution structure of the channel to a circulant one. Due to application of CP, the OFDM block exhibits cyclostationarity statistically [68]. The total number of samples in an OFDM symbol is denoted as N_s which is given by:

$$N_s = N_c + N_d \tag{3.7}$$

A beneficial and convenient property of the presence of CP in OFDM is to provide peaks in the autocorrelation of the received waveform. The peak value appears in the AuF at the lag of N_d samples, when a sequence of OFDM samples of minimum length $N_d + N_c$ is considered.

Many earlier studies have revealed that autocorrelation based detection provided by CP makes SS quite effective while the computational complexity remains rather low [47]. CP-autocorrelation method is also insensitive to NU issues.

AuF is non-zero at certain time lags, i.e. at $\tau = \pm N_d$ for some time instances, and zero for others, as shown in Figure 3.3 [4]. These nonzero autocorrelation coefficients can be used as log likelihood ratio test (LLRT) statistic in the low SNR regime [63]. This property makes it possible to achieve blind channel estimation [46], synchronization and blind equalization in CP-OFDM systems [53].

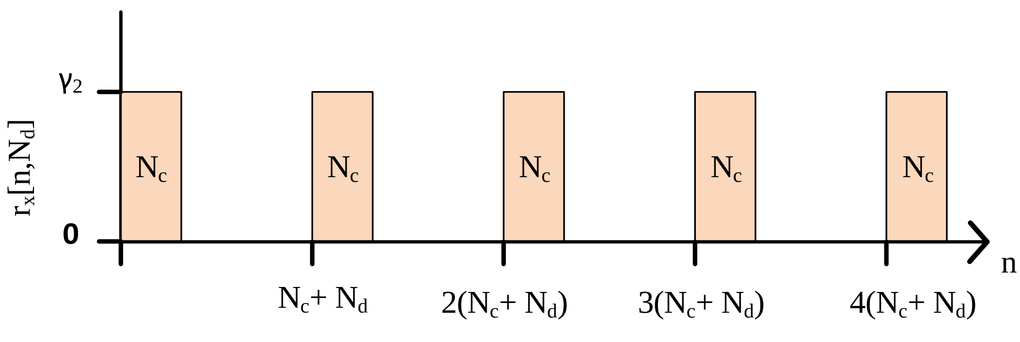

Figure 3.3. *Signal model for Periodic AuF for CP-OFDM.*

Data symbols which are being transmitted are assumed to have zero-mean be independent and identically distributed (i.i.d.) [61]. Figure 3.4 shows typical spectrum for a transmitted OFDM signal. FFT process is performed over the received CP-OFDM in order to decompose it to subbands [21, 53]. In a CR system, FFT can also be used as an analyzer to detect spectral holes in the electromagnetic spectrum [10]. Simplified block diagram of an OFDM system can be seen by Figure 3.5 [9, 66, 81].

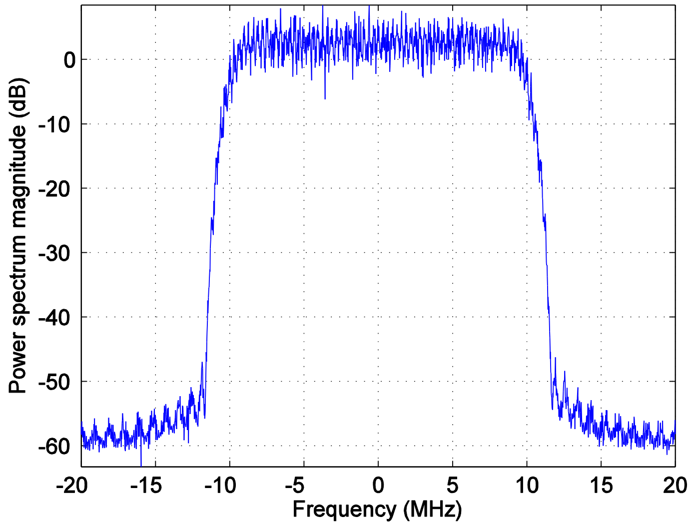

Figure 3.4. *OFDM signal spectrum.*

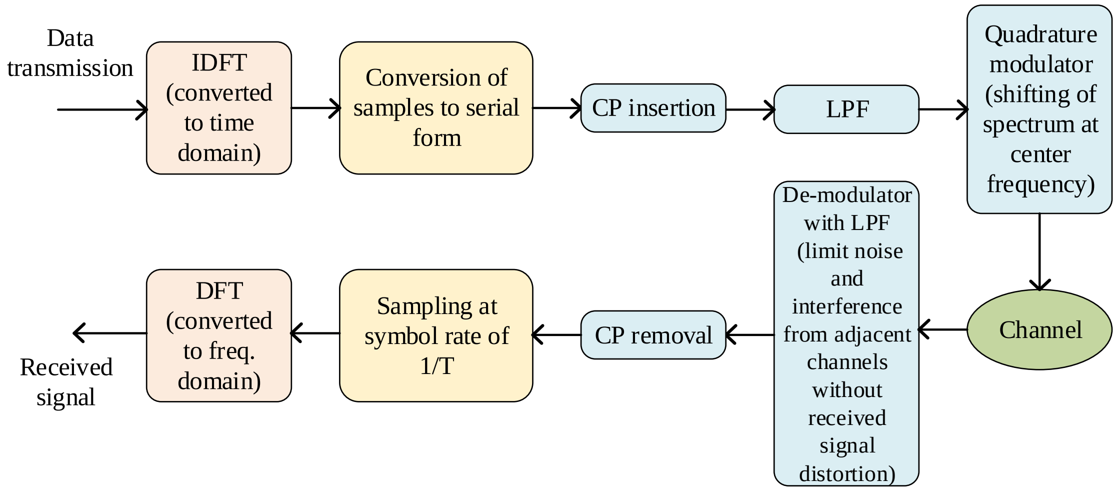

Figure 3.5. *Simplified block diagram of an OFDM system.*

3.3 Time-domain algorithms for autocorrelation based spectrum sensing

This section focuses on the analysis of the test statistic distribution and threshold setting calculation in the time domain operation of an autocorrelation based detector. The PU detection performance is evaluated analytically and verified by simulations.

3.3.1 Analytical calculation of threshold, false alarm and detection probabilities

As OFDM signal exhibits non-zero autocorrelation property, the autocorrelation coefficient in such systems is the ratio of samples of CP with overall samples of useful data length and it can be written as [14, 15]:

$$\mu = \frac{N_c}{N_c + N_d} \tag{3.8}$$

where μ is the autocorrelation coefficient. This can also be calculated from the time interval for useful data (T_u) and time interval for CP (T_c) [63] can be seen in Figure 3.6.

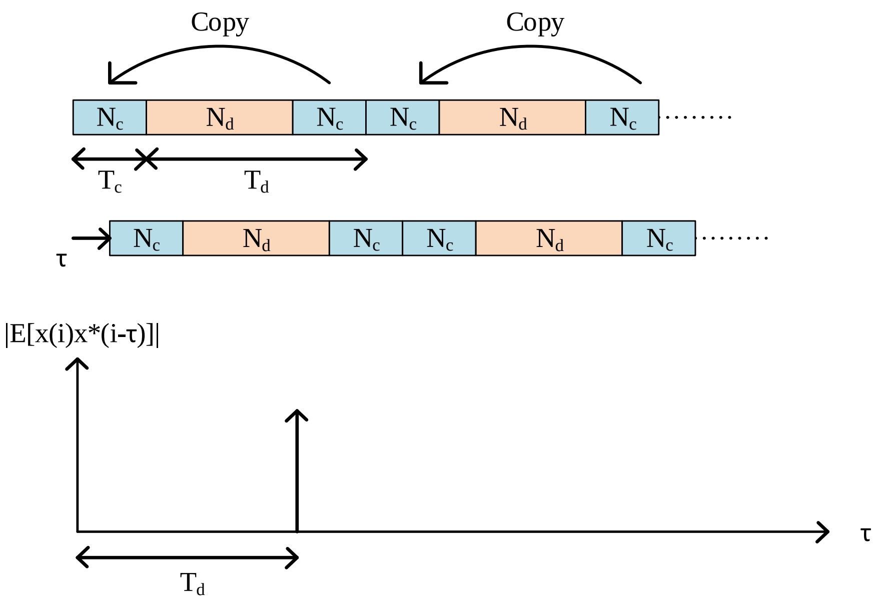

Figure 3.6. *OFDM block structure and idealized autocorrelation of an OFDM signal.*

AuF of the received signal is given by [16]:

$$R(\tau) = \frac{1}{N}\sum_{n=1}^{N} y(n)\, y^*(n+\tau) \tag{3.9}$$

where N is the total number of samples that are used to estimate AuF and $y[n]$ is the received OFDM signal. It is a convolution of the PU OFDM signal, denoted by $s[n]$, with the channel impulse response, $h[n]$, with zero mean, complex, circularly symmetric AWGN which is denoted by $w[n]$. Both the signal and noise are mutually independent of each other. Hence, $y[n]$ can be written in form:

$$y[n] = \overbrace{s[n] \otimes h[n]}^{x(n)} + w[n] \tag{3.10}$$

Here $x(n)$ is the PU signal with channel effects.

The main purpose of a CP autocorrelation based detector is to differentiate AWGN and samples of the OFDM signal, which have similar statistical properties, from each other. By the presence of CP, OFDM signals exhibit non-stationary property. Hence, AuF in eq. (3.9) becomes time-varying as shown in Figure 3.3. An assumption is made for the sensing receiver that it examines n_0 consecutive symbols of OFDM signal. Hence, the received sampled sequence length is given by [16]:

$$N = n_0 \times N_S \text{ samples.} \tag{3.11}$$

. The involved random processes have i.i.d distributions of samples, finite variances, and zero mean value of. Therefore, according to the central limit theorem (CLT) and assuming that the IFFT has relatively large size, eq. (3.10) can be expressed as:

$$s(n) \approx \mathcal{N}_c\left(0, \sigma_s^2\right) \tag{3.12}$$

$$w(n) \approx \mathcal{N}_c\left(0, \sigma_n^2\right)$$

and

$$y(n) \approx \mathcal{N}_c\left(0, \sigma_s^2 + \sigma_n^2\right)$$

where ${\sigma_s}^2$ is the variance of the PU signal and ${\sigma_n}^2$ is the variance of noise. $\mathcal{N}_c(.)$ illustrates that it has complex Gaussian distribution [17, 21, 35, 53, 57].

The case of known PU signal: When the PU OFDM signal characteristics are known, we expect to find the correlation peak at time lag N_d. The CP changes from sample to sample, so the AuF at the time lag of N_d will also be random. Hence, this random variable, called decision statistic, is given by:

$$r = R(\tau)|_{\tau = \pm N_d} \tag{3.13}$$

As the noise is white and it has zero mean, the expectation of r_w (the decision statistic in the noise only case) is zero for any $\tau \neq 0$.

There are two factors which determine the performance of the SS function. One is the probability of detection (P_D) and the other one is the probability of false alarm (P_{FA}). In case of (correct) detection, the CR network tells SUs that the spectrum is not available due to the presence of a PU, when indeed spectrum is occupied by PUs. But, in case of false alarm, the PU signal is not present in reality and spectrum is free to use, but the SS function claims that the spectrum is already occupied. This type of false detection of a PU signal reduces the efficiency of spectrum use, but it causes no interference with authorized users. Another type of mistake in SS is missed detection and this is the most serious case as it introduces interference to the primary user. The probability of missing the PU (P_M) can be expressed as $P_M = 1 - P_D$ [22].

A Neyman-Pearson (NP) test is used to analyze the detection problem of the PU signal and it comprises two statistical hypotheses: hypothesis 0 (H_0) and hypothesis 1 (H_1). The two NP test cases are defined as [2]:

$$y(n) = \begin{cases} w(n) \mid H_0 \\ k_0 s(n) + w(n) \mid H_1 \end{cases} \qquad 0 < t \le T \tag{3.14}$$

where k_0 is an SNR scaling factor, H_0 means that PU is not active and H_1 means PU is active. It can be seen that under hypothesis H_0, $y(n)$ consists of only of $w(n)$ in absence of PU whereas the PU signal $s(n)$ is present along with $w(n)$ under hypothesis H_1.
Using the idea of Figure 3.3 in Section 3.2, a test statistics, T_ρ, is derived that is the maximum likelihood estimate (MLE) of the autocorrelation coefficient of $y(n)$ at lag N_d, which may be written as [14, 15, 44, 48]:

$$T_\rho = \frac{\frac{1}{N}\sum_{n=0}^{N-1} R\left\{y(n)\,y^*(n+N_d)\right\}}{\frac{1}{N+N_d}\sum_{n=0}^{N+N_d-1} |y(n)|^2} \tag{3.15}$$

Here $R\{.\}$ is real part of complex samples and $\{.\}^*$ is the complex conjugate of the value. The total number of samples used for the autocorrelation is $N + N_d$. In SS calculations, the mean of $y(n)$, which is denoted by $E\left[y(n)\right]$, and the variance of $y(n)$ under H_0 are given by:

$$E\left[y(n)\right] = 0 \tag{3.16}$$
$$\mathrm{var}\left[y(n)\right] = \frac{1}{N}$$

Under H_1, the mean of $y(n)$ and its variance are given by:

$$E\left[y(n)\right] = \rho$$
$$\mathrm{var}\left[y(n)\right] = \frac{\left(1-\rho^2\right)^2}{N} \tag{3.17}$$

where ρ is in the form of:

$$\rho = \frac{N_c}{N_d + N_c} \cdot \frac{\sigma_s^2}{\sigma_s^2 + \sigma_w^2} . \tag{3.18}$$

Eq. (3.18) can be rewritten as:

$$\rho = \frac{N_c}{N_s} \cdot \frac{\sigma_s^2}{\sigma_x^2} \tag{3.19}$$

As the distribution of OFDM underutilization is already known, this is the reason P_D can be increased under particular P_{FA}. These probabilities are given by:

a) Detection Probability P_D:

$$P_D = P\left(T_\rho > \lambda_\rho \mid H_1\right) \tag{3.20}$$

b) False alarm Probability P_{FA}:

$$P_{FA} = P\left(T_\rho > \lambda_\rho \mid H_0\right) \tag{3.21}$$

where λ_ρ is the threshold used by the detector. The threshold value can be calculated when the target P_{FA} in sensing is fixed and the number of samples in PU sensing is known.

According to eq (3.16) and eq. (3.17), the probability density function (PDF) of $y(n)$ can also be estimated based on CLT and it shows that it has Gaussian distribution which is given in the form of NP test as [14, 15, 17]:

Under H_0:

$$H_0 : T_\rho \approx \mathcal{N}_R\left(0, \frac{1}{N}\right) \tag{3.22}$$

Under H_1:

$$H_1 : T_\rho \approx \mathcal{N}_R\left(\rho, \frac{\left(1-\rho^2\right)^2}{N}\right) \tag{3.23}$$

where $\mathcal{N}_R$ refers to the Gaussian distribution for real valued numbers.

Because of the Gaussian statistics, T_ρ has a probability of exceeding the threshold, λ_ρ, that can be calculated as:

$$P\left(T_{\rho} > \lambda_{\rho}\right) = \frac{1}{2} erfc\left(\frac{\lambda_{\rho}}{\sqrt{2}\sigma_{r}}\right) \tag{3.24}$$

where $erfc(.)$ denotes the complimentary error function. Based on this probability function, its result is used as test statistics for OFDM signal in order to detect PU signal from desired spectrum under a very low SNR system, i.e., when the power of noise dominates the signal power $\left(\sigma_{n}^{2} >> \sigma_{s}^{2}\right)$. The distribution of test statistics in this case becomes [14, 16]:

$$P\left(T_{\rho} > \lambda_{\rho} \mid H_{0}\right) = \frac{1}{2} erfc\left(\sqrt{N}\lambda_{\rho}\right) \tag{3.25}$$

Using eq. (3.21), the expected value of T_{ρ} under the null hypothesis is zero. Eq. (3.25) gives the probability of false alarm, P_{FA} when the detection of AWGN samples takes place under hypothesis H_{0}. Thus from eq. (3.21) and eq. (3.25), threshold λ can be expressed as:

$$\lambda_{\rho} = \frac{1}{\sqrt{N}} erfc^{-1}\left(2P_{FA}\right) \tag{3.26}$$

Eq. (3.23) is used to calculate test-statistics which correspond to the evaluation of P_{D} of a PU signal in form of OFDM signal, which can be expressed as:

$$P\left(T_{\rho} > \lambda_{\rho} \mid H_{1}\right) = \frac{1}{2} erfc\left(\sqrt{N}\frac{\lambda_{\rho} - \rho}{1-\rho^{2}}\right) \tag{3.27}$$

Eq. (3.27) shows that detection probability of a PU signal in an autocorrelation based detector is calculating by using:

- Information of a threshold value of the detector,
- Variance of OFDM signal used as PU signal,
- Complete information about the OFDM signal structure, i.e., the CP length N_{c} and the useful symbol duration N_{d},
- Autocorrelation length N ,
- Variance of noise.

It can be seen that it is necessary to know the information of useful data samples of OFDM PU signal in order to detect PU signal in the given spectrum. If this information is not known, then AuF can be calculated by using several candidate values (based on knowledge of alternative PU OFDM configurations) for the useful symbol length $\tau = N_{d}$. SU determines the variance calculated in eq. (3.18) from the received signal at the sensing station. This method proves to be quite efficient by having low computational complexity, and as it needs limited information about the PU signal for detection [16].

In later case studies, the P_{FA} value is predefined and set to 0.1. The SNR scaling factor, which has been used in calculations in eq. (3.14) is given by:

$$k_0 = qSNR = 10^{(SNR/10)} \quad . \tag{3.28}$$

The SNR range of -30 dB to 5 dB is used in simulations.

In case of ED, which has been used as a reference detector, the threshold value is calculated by:

$$\lambda_{ED} = \frac{\left(1 + Q^{-1}\left(P_{FA}\right)\right)}{\sqrt{N}} \tag{3.29}$$

$$\lambda_{ED} = \frac{\left(1 + Q^{-1}\left(0.1\right)\right)}{\sqrt{N}} \tag{3.30}$$

where P_{FA} is set to be 0.1.

The two probabilities of P_D and P_{FA} in ED are given by:

$$P_{D-ED} = Q\left(\frac{\left(\lambda_{ED} - \left(qSNR + 1\right)\right) \times \sqrt{N}}{qSNR + 1}\right) \tag{3.31}$$

and

$$P_{FA-ED} = Q\left(\frac{\left(\lambda_{ED} - 1\right) \times \sqrt{N}}{1}\right) \tag{3.32}$$

3.4 Novel frequency domain CP autocorrelation based CSS method

It is a common assumption that the SS bandwidth is equal to the full bandwidth potentially occupied by the PU. In other words, an active PU uses the whole available spectrum without any interference from other signals in a certain frequency band. The sensing band can contain a PU signal together with white Gaussian noise or only noise in the whole frequency channel. However, a realistic CR scenario differs from this common assumption, and there may exists some locally operating SUs which are present and utilizing part of frequency band inside the broadband PUs frequency channel, see Figure 3.7 for an example. Such situation may arise, for example, when the other SU system has failed to detect the PU, or in the case of a reappearing PU before the SU systems have detected it. Quiet periods are commonly assumed to be used by active SUs to enable the detection of reappearing PUs, but it may be difficult to synchronize the quiet periods of independent SU systems, and such a situation may arise. Generally, effective sensing methods for scenarios like Figure 3.7 could be useful tools for CR developments.

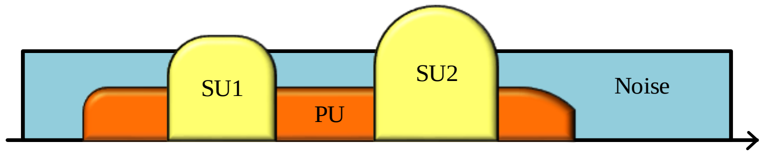

Figure 3.7. *Spectrum utilization scenario in the presence of uncoordinated secondary systems.*

Basically, the autocorrelation of the received waveform is a time-domain operation, but in the situation of Figure 3.7, time domain autocorrelation based SS method is expected to fail. One may try to compute the autocorrelation in the time domain for clean part(s) of PU signal band only, but this would involve additional complicated filtering in the receiver. Due to this reason, frequency domain implementation of autocorrelation based method is proposed in this study and this method proves to be a better solution in such situations. The frequency-domain method exploits subband samples obtained by FFT processing for the computation FD-AC [33]. Hence, this method raises a great interest in CR systems as it utilizes 'clean' parts of PU spectrum only, which are unoccupied by SUs, and where SUs are not interfering with the PUs.

The FD-AC based method provides a partial band sensing of the PU signal. Hence, it makes possible to detect partially overlapping PUs. Alternatively, partial band autocorrelation computation from subcarrier samples can be utilized, in the spirit of compressed sensing, in order to reduce the computational complexity or simplify the analog-to-digital conversion interface, e.g. by using multiple narrowband (and low-cost) ADCs in the sensing.

In the frequency domain, autocorrelation calculation is performed over subband samples at the output of the FFT process. In an FFT based receiver, AuF for a specific time lag τ, normalized to FFT domain sample interval of subcarrier, can be implemented effectively from the subband samples in FFT domain as:

$$C_Y(\tau) = \frac{1}{M}\sum_{m=1}^{M}\sum_{k\in\Omega} y_{k,m}{}^{*} \cdot y_{k,m+m_\Delta} e^{-j2\pi\tau k} \tag{3.33}$$

$$= \frac{1}{M}\sum_{k\in\Omega}\left(\sum_{m=1}^{M} y_{k,m}{}^{*} \cdot y_{k,m+m_\Delta}\right) e^{-j2\pi\tau k} \tag{3.34}$$

where $y_{k,m}$ is the FFT output. Here $k = 0,\dots,K-1$ is the subband index (output samples of subbands), m is the subband sample index, Ω is the set of K_{comp} subcarriers which are used, and M is the integration length in FFT subband samples. Furthermore, K is FFT size of the sensing receiver, and it is considered as independent of the IFFT size of the PU transmitter. In addition, the number of subcarriers used in the FD-AC calculation, K_{comp} can be chosen as different values to reach the required sensing performance with minimum complexity while avoiding the use of interfered subbands.

Eq. (3.34) is a computationally efficient for of eq. (3.33), which indicates the possibility of using different subcarrier samples in the basic autocorrelation calculation, with the spacing of m_Δ. This helps to maximize the correlation observation for different combinations of the PU OFDM symbol duration and FFT based subband sample interval. Actually, the lag can be expressed in high-rate samples as:

$$N_d = \left(m_\Delta + \tau\right).M \tag{3.35}$$

Here m_Δ is a coarse value of the lag as an integer number of the subcarrier samples and τ is the fractional part of the lag, which appears in eq. (3.33) as a linearly frequency dependent phase term.

This AuF in eq. (3.34) is very efficient in terms of its computation. It shows that during calculation of basic AuF, a different number of subband-wise autocorrelations are averaged to enhance the correlation peak.

In the context of SS, the subband signals can be expressed as follows:

Under H_0:

$$y_{k,m} = w_{k,m} \tag{3.36}$$

Under H_1:

$$y_{k,m} = x_{k,m} + w_{k,m} \tag{3.37}$$

Here,

$$y_{k,m} = FFT[y\left(m.K\right),...,y\left(\left(m+1\right).K-1\right)] \tag{3.38}$$

and:

$$x_{k,m} \cong H_k s_{k,m} \tag{3.39}$$

where $x_{k,m}$ is the PU information signal at the m^{th} FFT output sample in subband k, H_k is the complex gain of subband k, and $w_{k,m}$ is the corresponding noise sample.

Furthermore, it is assumed that:

$$w_{k,m} \approx \mathcal{N}\left(0, \sigma_{w,k}^2\right) \tag{3.40}$$

$$x_{k,m} \approx \mathcal{N}\left(0, \sigma_{x,k}^2\right) \tag{3.41}$$

where $\sigma_{x,k}^2$ denotes the PU signal variance in subband k and $\sigma_{w,k}^2$ denotes the noise variance in subband k.

Since FFT is used for spectrum analysis, the subband noise variances can be assumed to be the same and can be written as:

$$\sigma_w^2 / K \cong \sigma_{w,k}^2 . \tag{3.42}$$

In an addition to the proposed algorithm for a PU signal with known CP-OFDM parameters, a similar idea can be applied for the case of unknown time lag in the AuF. If the lag values are considered with the time resolution of the FFT input, then the outer summation in eq. (3.34) can be interpreted as an IFFT. In the known lag case, only one element of the IFFT needs to be calculated. In the unknown lag case, the whole IFFT is calculated, and the test statistic value T_ρ is taken from the second maximum peak (the first one is the peak at zero-lag which is known as classical autocorrelation). Simulation results of this case are also given in Chapter 5.

The test statistic for both algorithms is taken from the magnitude of the AuF with the corresponding lag. It is also noted here that we use magnitude instead of real part because any frequency offset of the PU signal introduces phase rotation to the autocorrelation. This results in a phase rotation of the correlation peak, and its real part might even vanish with specific values of the frequency offset. In SS scenarios, it cannot be assumed that the sensing station is synchronized to the PU signal in real scenarios.

FD-AC based detector approach is extremely efficient to use due to its following advantages:

- Robust to NU,
- Good performance under the frequency selective channel compared with ED,
- Facilitates a partial band (i.e., compressed) sensing in the frequency domain.

These benefits can be seen in simulation results in Chapter 5.

3.5 Compressed spectrum sensing technique for reduction of complexity in spectrum sensing

Instead of necessity of all data to detect PU signal, CSS method can recover certain signals by using very few samples or measurements. Thus, this method is against a common approach of the data acquisition. This idea is used in this study to adapt the FD-AC to sensing scenarios where the PU signal spectrum is only partially used for sensing. This facilitates the use of FD-AC in scenarios like Figure 3.7 and it also helps to reduce the computational complexity and develop alternative sensing receiver structures also regarding analog RF and ADC modules. This technique exploits sparsity when observing the signal spectrum. Basically, the method performs compressive sampling in the spectral domain [33, 64].

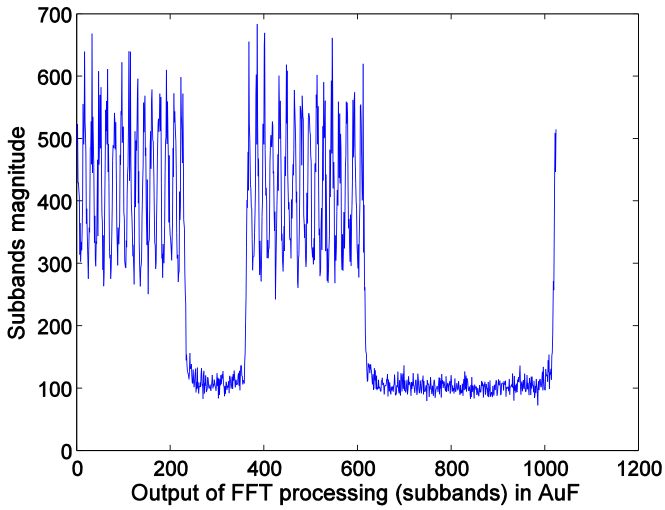

Figure 3.8. *Non-contiguous OFDM signal spectrum used as PU signal model in simulations as seen at the output of FFT processing of a sensing station. The sensing bandwidth is 20 MHz and 1024 point FFT is used for sensing.*

Figure 3.8 shows the output of FFT processing when it has been used in FD-AC method at a sensing station. The PU signal model is non-contiguous OFDM, with two sets of contiguous active subcarriers. The PU signal is considered to have sparse spectrum, and CSS methods are applicable. In this study, $K_{comp} = 242$ subbands (subbands between 369 and 609) have taken into account while evaluating CSS element. The CSS method uses less measurement of data but still recovers the same signal by using only small amount of data [28, 33, 72].

4. SYSTEM MODEL AND SIMULATION ENVIRONMENT

In this study, FD-AC based detection method is applied in a CR system in order to sense the electromagnetic spectrum for CP-OFDM type PU signals. It gives good sensing performance with high as well as low SNR values, and NU does not affect the performance of this detector significantly. This is due to the reason that it can easily differentiate between a CP-OFDM type communication signal and noise in low SNR range as well [28, 33]. It is advanced and more efficient technique compared with ED which is used in this study as a reference method. This detector works effectively in high SNR values but its performance degrades at low SNR values in the presence of NU. This detector is not able to distinguish between the signal and noise, and the detection is based on comparing the total measured power to the expected noise power. In this chapter, system models for both FD-AC based method and traditional ED are presented. As discussed already, FD-AC based method has is also used by adding CSS element with it, in order to reduce the computational complexity while using the detector. This study is paying more focus on the comparative analysis of all these methods when looking at low SNR values including NU challenges. All these methods are focusing on sensing PU signal if it is present or absent in available spectrum. In case when PU is absent, then CR shares the spectrum with SU without making any interference to PUs.

In our simulation model, a CP-OFDM acts as the PU signal when evaluating the SS methods. This signal scheme facilitates FD-AC method due to the presence of CP. In case of unknown CP-OFDM parameters, the second maximum peak is determined and detected by the FD-AC method. The reason for second maximum peak is that the first peak is at zero-lag, which is always present in the AuF.

Most of the researchers assume a flat fading channel in their SS related studies in order to make calculations simple. Hence, they don’t consider noise variance uncertainty and a frequency selective channel, as these issues makes trouble to sense PU signal [26]. But, in this study, AWGN as well as frequency selective channel and noise uncertainty have also been added as a subjects to consider, so as to make more realistic performance evaluation, as can be seen in the following results.

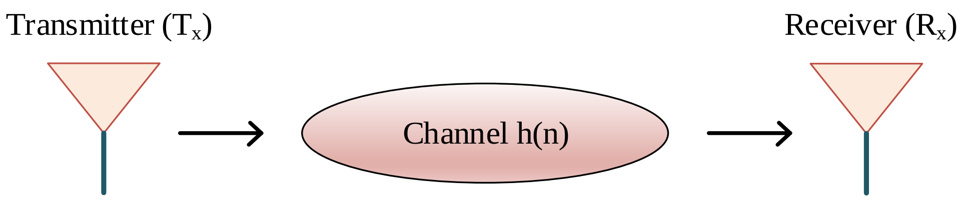

Figure 4.1. *Signal transmission and reception mechanism.*

In Figure 4.1, it can be seen that one transmitter and one receiver are used for the transmission of data. CP-OFDM signal is used for its wide range of applications and due to its ability to facilitate the FD-AC based method. We consider the flat fading case, which is an ideal scenario, as well as realistic case with a frequency selective channel to transmit data. There can also be many noise uncertainties in environment, so these cases can be shown as follows:

➢ **Type 1: Flat fading channel:**

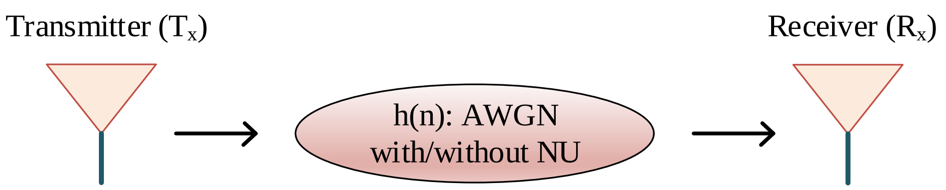

Figure 4.2. *Signal under AWGN in presence or absence of noise variance uncertainties.*

➢ **Type 2: Frequency selective channel:**

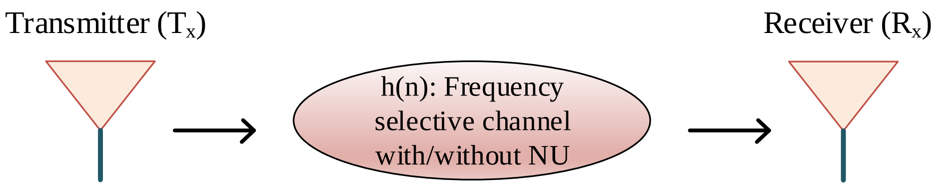

Figure 4.3. *Signal transmission and reception under frequency selective channel.*

The frequency selective channels that have been considered in this study are [add reference]:

- An Indoor channel model,
- SUI-1 channel model and
- ITU-R vehicular A channel model.

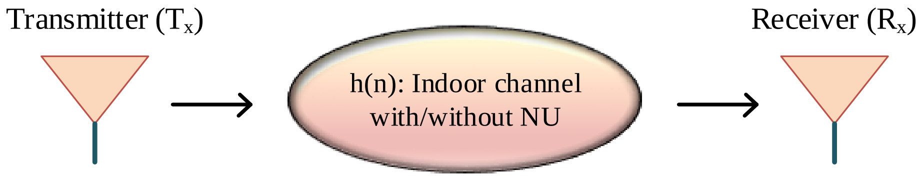

Figure 4.4. *Signal transmission and reception under frequency selective channel of indoor model.*

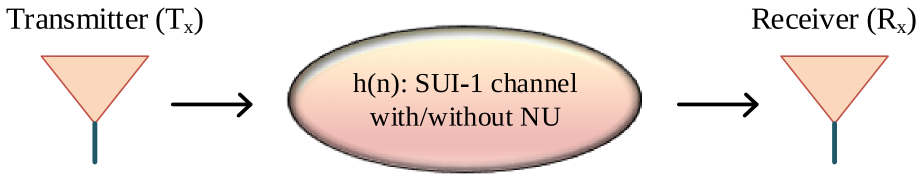

Figure 4.5. *Signal transmission and reception under frequency selective channel of SUI-1 model.*

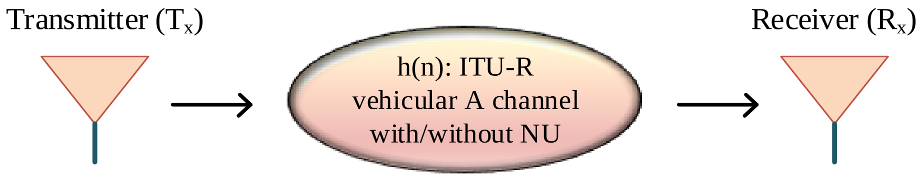

Figure 4.6. *Signal transmission and reception under frequency selective channel of ITU-R vehicular A channel model.*

In these channels, the received power level suffers from effects of path loss over the wireless link. Various attenuation and distortion effects can occur due to non-line of sight propagation, fading, shadowing, and many other propagation factors, as already been discussed in Section 1.1. FD-AC based detector has been used in this study as it is robust to propagation effects.

Algorithms which are used for testing the detectors are working on a large number of Monte Carlo simulation loops in order to get reliable test results. An overview of each detector method which is used in this study can be easily comprehended from the following block diagrams.

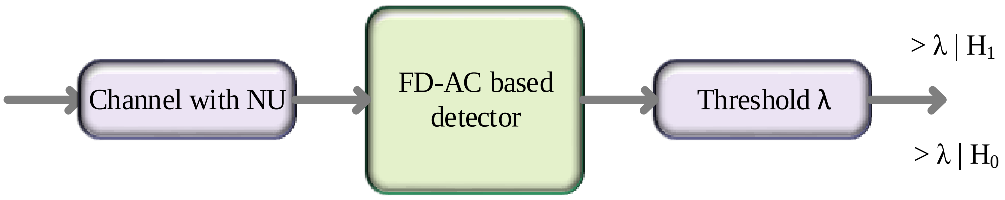

Figure 4.7. *A block diagram of FD-AC based detector in CRN system model.*

When CSS element is used in the processing while detecting PU signal by FD-AC based method, in such conditions block diagram can also be shown as:

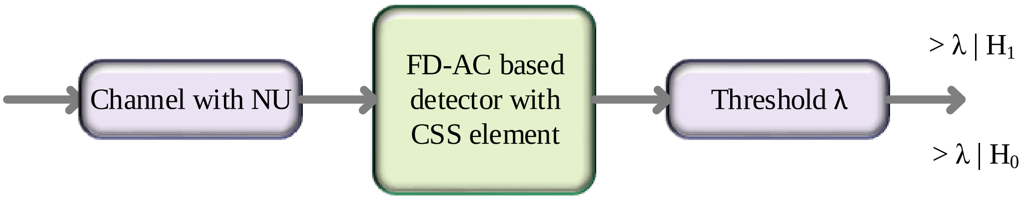

Figure 4.8. *A block diagram of FD-AC based detector in presence of CSS element in CRN system model.*

As ED has also been used in this study for comparison analysis of FD-AC based detector with it, a block diagram of traditional ED is given by:

Figure 4.9. *A block diagram of traditional ED in CRN system model.*

These are the generic block diagrams which briefly explain the scenarios in which these methods are tested to sense PU signal from electromagnetic spectrum. The overall simulation scenario is illustrated in the block diagram of Figure 4.10.

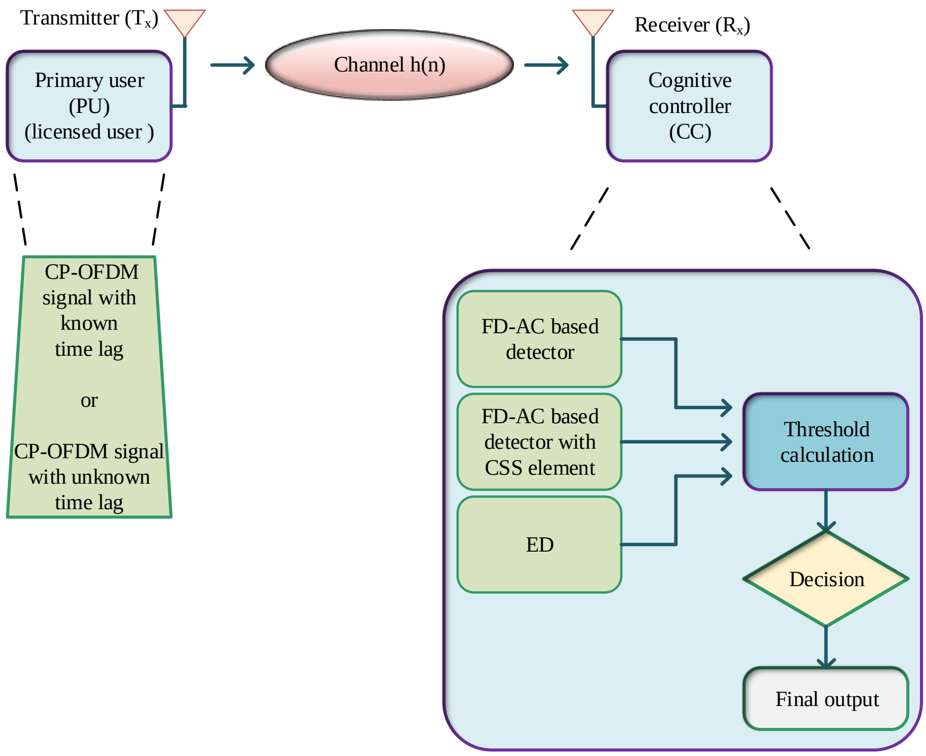

Figure 4.10. *Simulation model of traditional ED and proposed FD-AC based CRN*

4.1 Problem formulation

In order to check the processing of FD-AC based method, it can be explained as follows:

In step 1:

Noise and an OFDM signal are generated. Noise is taken into account as hypotheses 0, whereas a signal with channel and some added noise is taken into account as hypothesis 1. A received signal in each hypothesis is given by:

$$H_0 : y(n) = w(n) \tag{4.1}$$

$$H_1 : y(n) = s(n) \otimes h(n) + w(n) \tag{4.2}$$

where $y(n)$ is the received signal by the sensing station, $s(n)$ is the transmitted signal by PU (CP-OFDM signal), $h(n)$ is a frequency selective channel (constant in the AWGN case or Indoor channel model, SUI-1 channel model or ITU-R Vehicular A channel model) and $w(n)$ is noise, which is assumed to be AWGN. It has a constant power spectral density which can be expressed as W/Hz (watts per Hertz of bandwidth (BW)) and its amplitude has a Gaussian distribution. Due to constant power spectral density, it is called as white noise.

SNR is basically the ratio of the power of PU signal to noise power which can be written as:

$$SNR = \sigma_X^2 \; / \, \sigma_n^2 \tag{4.3}$$

In dB, it can be written in form:

$$SNR_{dB} = 10\log_{10}\left(SNR\right) \tag{4.4}$$

In step 2:

The autocorrelation based detector is used in the frequency domain. For this purpose, a signal in step 1 is converted to the frequency domain using FFT process. AuF is applied on its output and then IFFT process is used to convert it back to the time domain.

Under H_1:
$$r_{yy}\left(n\right) = AuF\left(y\left(n\right)\right) \tag{4.5}$$

Under H_0:
$$r_{ww}\left(n\right) = AuF\left(w\left(n\right)\right) \tag{4.6}$$

In step 3:

- For a known signal:

Known time lag is used as the test-statistic when the OFDM signal parameters are known.

$$T\left(y\right) | H_1 : T_{yy} = r_{yy}\left(N_d + 1\right) \tag{4.7}$$

$$T\left(w\right) | H_0 : T_{ww} = r_{ww}\left(N_d + 1\right) \tag{4.8}$$

- For OFDM signal with unknown parameters:

Maximum value of the peak after zero lag is used as the test-statistic:

$$T\left(y\right) | H_1 : T_{yy} = r_{yy}\left(N_{peak}\right) \tag{4.9}$$

$$T\left(w\right) | H_0 : T_{ww} = r_{ww}\left(N_{peak}\right) \tag{4.10}$$

Here $\left(N_{peak}\right)$ is time lag of the maximum peak with nonzero lag.

In step 4:

Calculation of a threshold (λ) value takes place. This calculation is according to experiential results based on target P_{FA}: ($P_{FA} = 0.1$).

In step 5:

A decision device compares the test-statistics with threshold value and then gives P_D and P_{FA} under both H_1 and H_0 hypotheses, respectively.

$$P_D = P\left(T\left(y\right) > \lambda \mid H_1\right) \tag{4.11}$$

$$P_{FA} = P\left(T\left(w\right) > \lambda \mid H_0\right) \tag{4.12}$$

This processing of FD-AC is clearly shown in flow diagrams. There are four cases that have been considered in this study for autocorrelation based SS technique to work in the frequency domain.

The processing of FD-AC based method can more clearly be shown in flow diagrams shown in Figures.

Case 1:

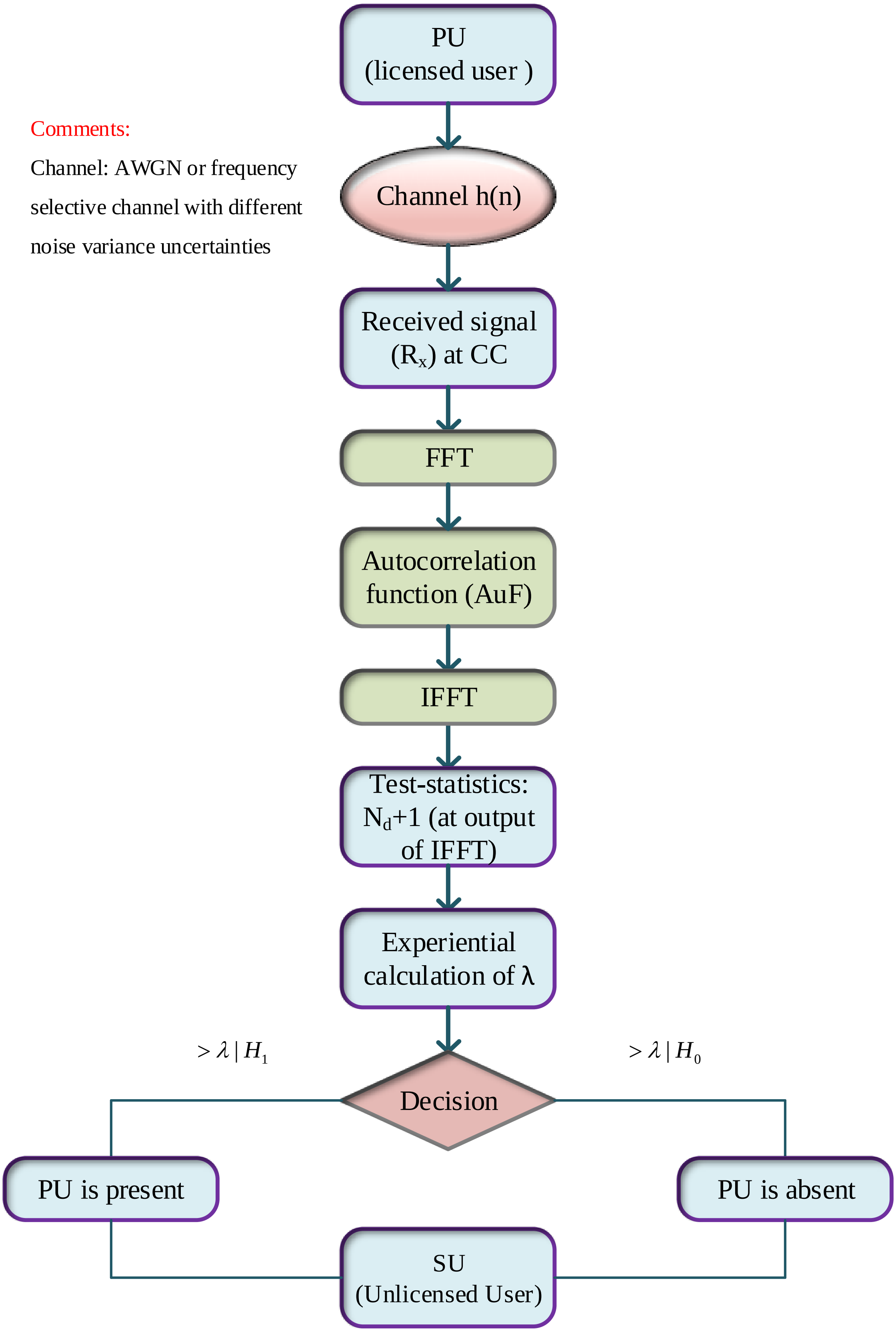

Figure 4.11. *FD-AC based SS technique in absence of CSS element with a known time lag.*

Case 2:

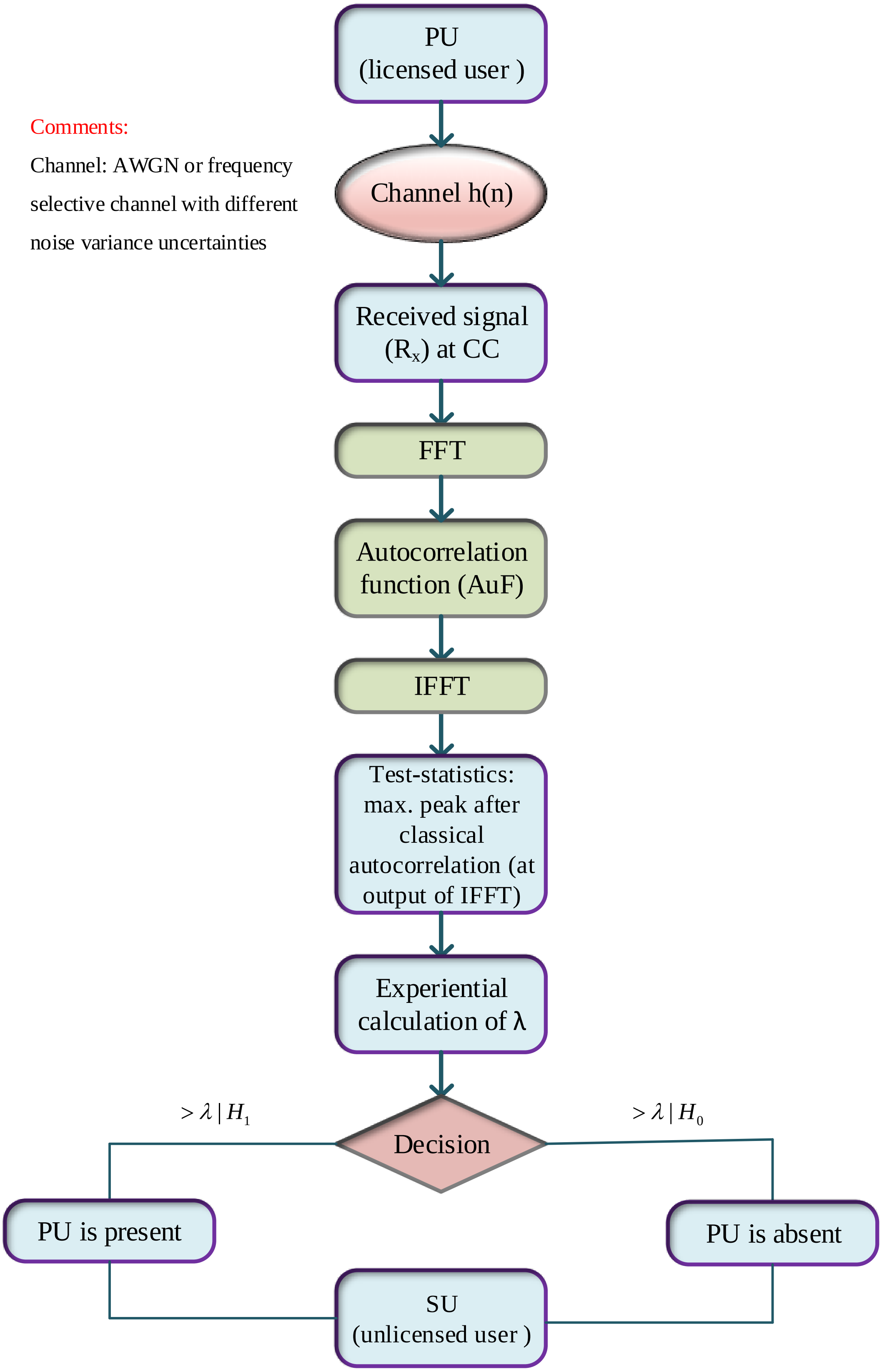

Figure 4.12. *FD-AC based SS technique in absence of CSS element with an unknown time lag.*

Case 3:

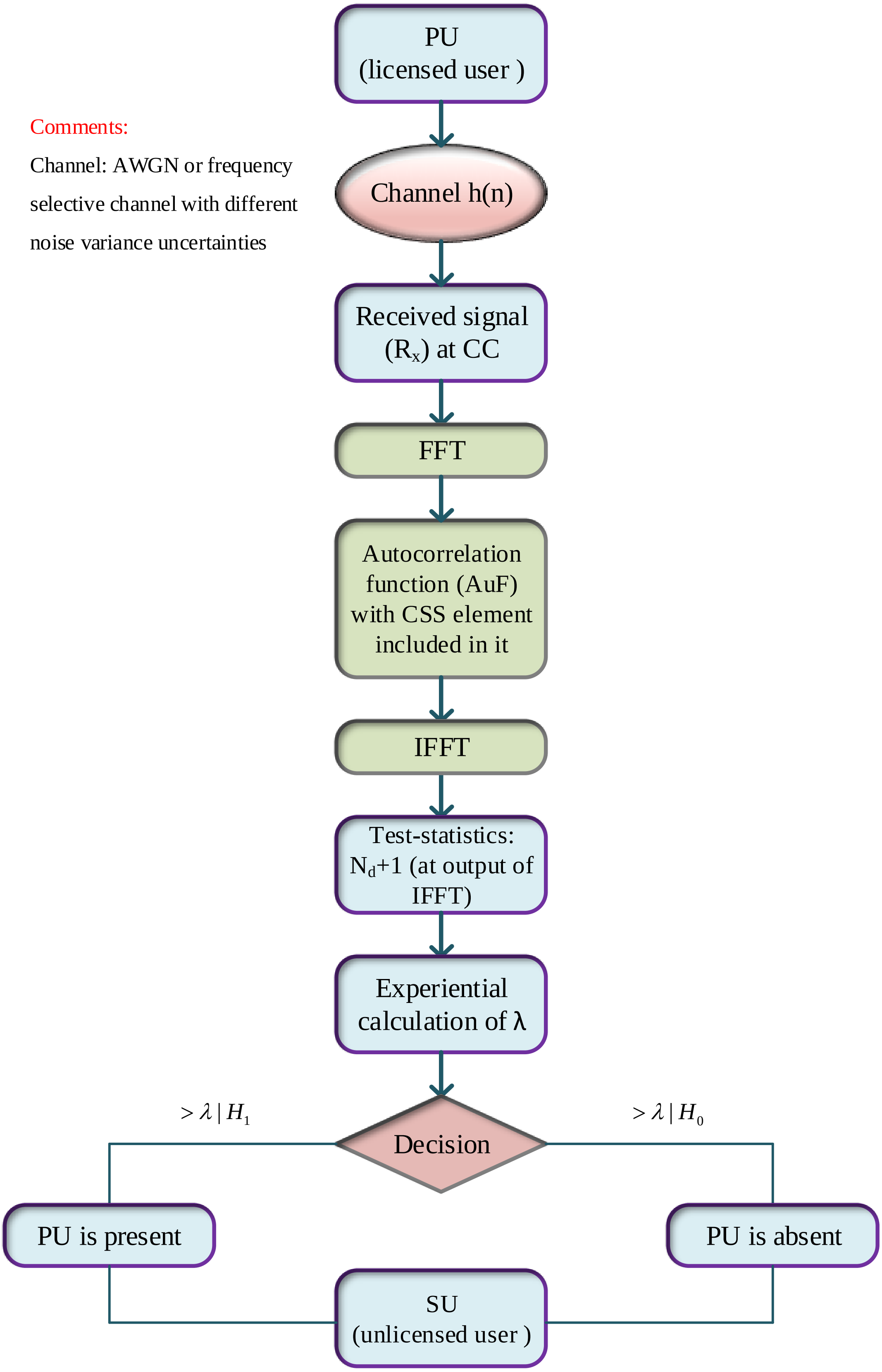

Figure 4.13. *FD-AC based SS technique in presence of CSS element with a known time lag.*

Case 4:

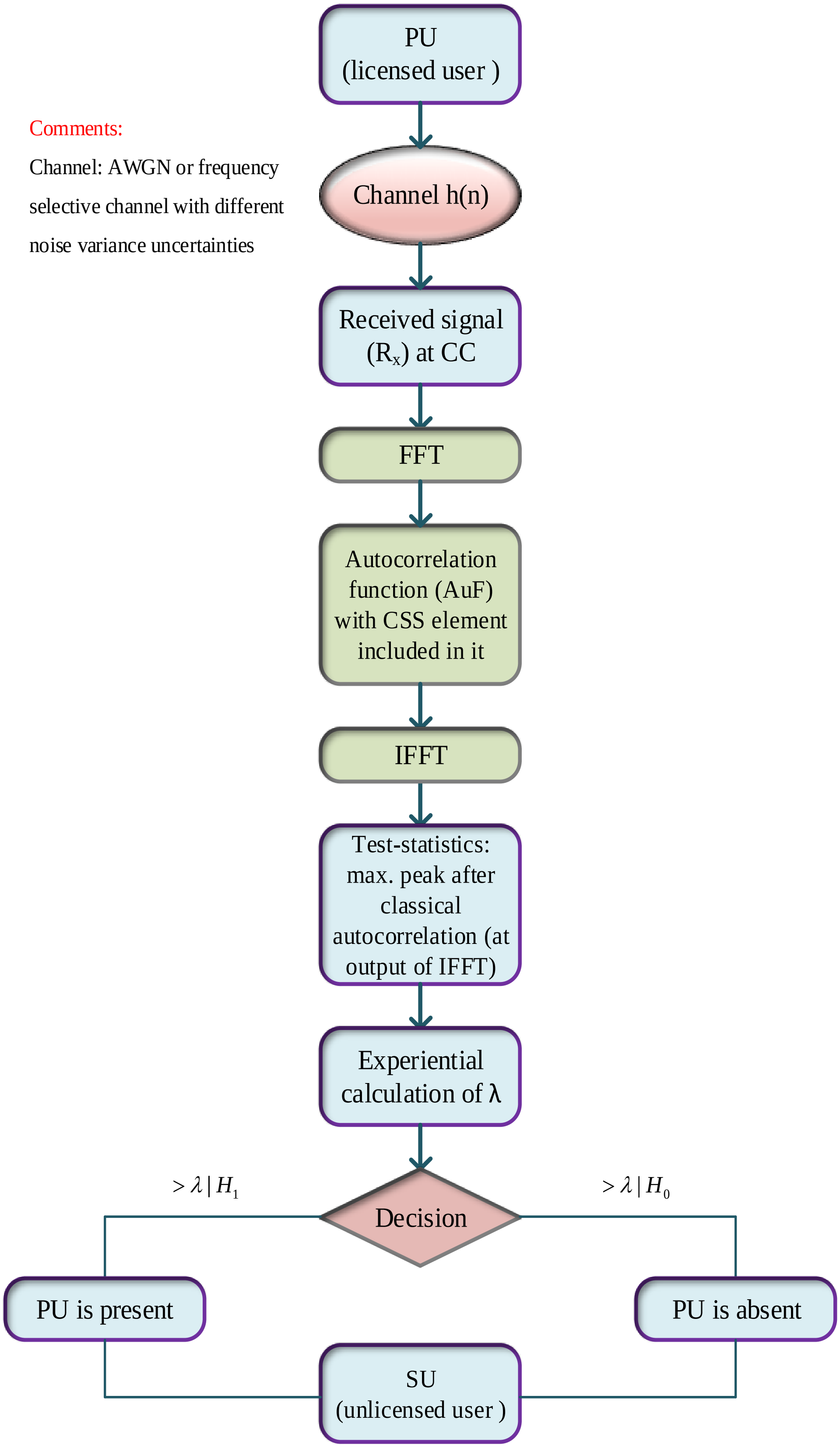

Figure 4.14. *FD-AC based SS technique in presence of CSS element with an unknown time lag.*

The simulation studies of this thesis are based on system parameters given in Table 4-1.

Table 4-1. *Parameters of signal model for both traditional and proposed algorithms.*

- OFDM symbol duration: $N_d = 64$ samples
- Length of CP for OFDM: $N_c = 16$ samples
- Number of active OFDM subcarriers: 31 subcarriers
- Number of samples of one OFDM symbol: $N_s = N_d + N_c = 80$
- Number of OFDM symbols in sensing: 1280
- Target $P_{FA} = 0.1$
- Number of FFTs averaged for correlation: $M = 100$
- Subcarrier sample offset: $m_\Delta = 0$
- Size of FFT (number of subbands) in FD-AC sensing part: $K = 1024$
- Total number of samples in sensing $\left(M + m_\Delta\right)K = 102400$
- Number of subbands used in CSS: $K_{comp} = 242$ subbands (368:609)

The OFDM signal uses 20 MHz bandwidth and all used channel models are parametrized for the same. The OFDM signal spectrum is shown in Figure 4.15.

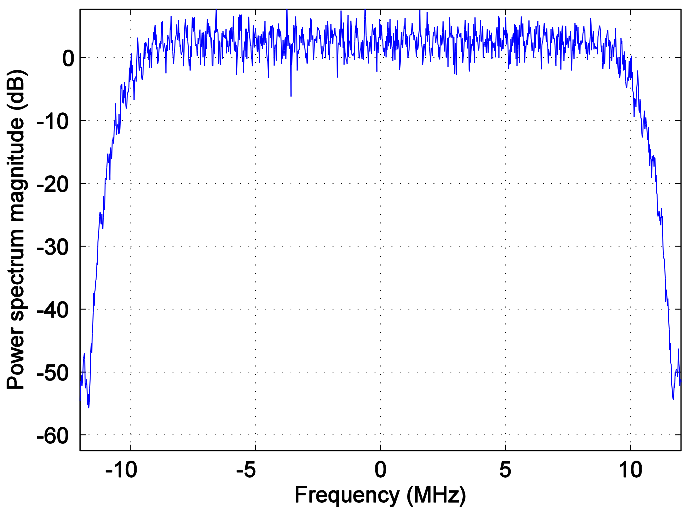

Figure 4.15. *OFDM signal of 20 MHz bandwidth.*

However, in our simulations, only 31 subcarriers of 64 are active. We consider a non-contiguous OFDM case where subcarriers 1…15 and 24…39 are active. The resulting power spectrum, as seen after the FFT of the sensing receiver is shown in Figure 4.16.

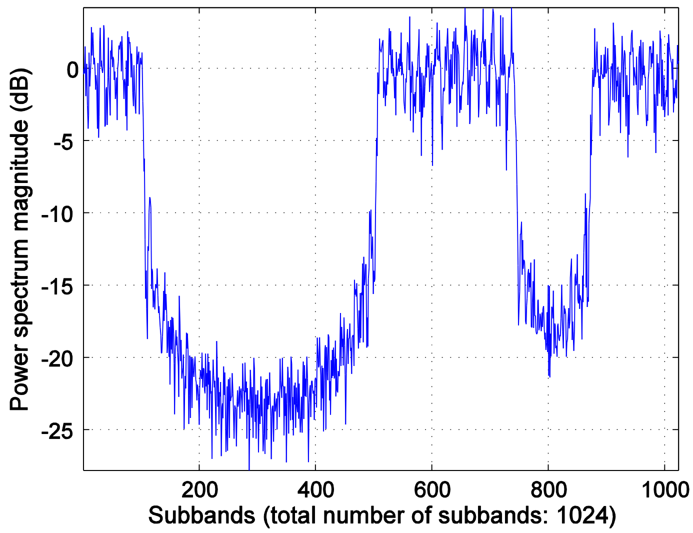

Figure 4.16. *Non-contiguous OFDM signal spectrum used as PU in simulations.*

For the useful OFDM symbol duration of N_d =64 samples, we expect to see the CP correlation peak at the lag of 64. This is utilized in FD-AC simulation cases based on known OFDM parameters. A typical simulated autocorrelation is shown in Figure 4.17, where a clear peak at the expected lag value can be observed. In the algorithm which assumes knowledge of the time lag, the AC is calculated only for the expected lag value. In the simulation cases with unknown OFDM parameters, the sensing receiver calculates AC for all possible lag values and chooses the non-zero lag value which gives the highest peak. This can be obtained effectively by taking IFFT of the constructed FFT-domain correlation.

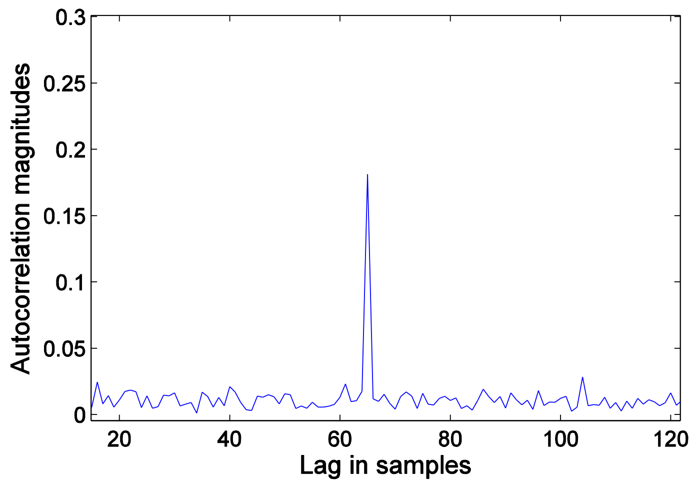

Figure 4.17. *Example of CP correlation obtained in simulations by FD-AC processing.*

In a case when the CSS is included in the FD-AC method, only 242 subchannels are used for constructing the AC in FFT domain. Using the same 242 as the IFFT length, an example of the resulting correlation is shown in Figure 4.18. Due to shorter IFFT length, the sample spacing of the discrete-time correlation (in seconds) is scaled by the factor *FFT length / IFFT length*. As a consequence, the expected lag for the correlation peak can be calculated as $242 \cdot 64/1024 = 15.125$, i.e., the correlation at lag 15 is assumed to take the highest value.

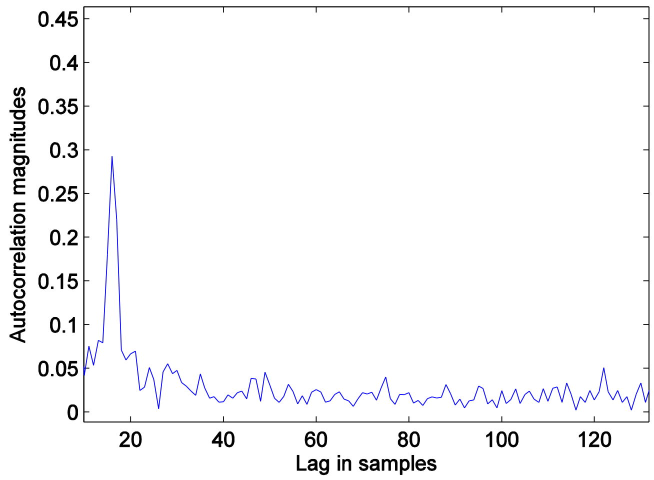

Figure 4.18. *Peak in CP-OFDM signal used by FD-AC method with CSS.*

In Figure 4.18, the correlation peak can be seen at the correct lag value. The connections between known and unknown OFDM parameter cases are quite similar as in the basic case without the CSS.

The target P_{FA} is set to 0.1 in all of the simulations in this study.

Frequency selective channel vs. flat fading channel

In flat fading, a channel spectral response is flat. In this case, coherence bandwidth of the channel is always greater than the bandwidth of the signal. Therefore, all frequency components of the signal experience the same magnitude of fading. But, in frequency selective fading, it has contrary characteristics compared with flat fading. In a frequency selective channel, it has smaller coherence bandwidth for the channel compared with bandwidth of the signal. Thus, each frequency component of the signal experience different fading. It has dips or fades in its channel spectral response. This is due to the fact that environment creates reflections of the signal which happens to cancel out certain frequencies in the receiver side. While transmitting a wide band signal, these dips in frequencies result in loss of the signal power. But, in OFDM transmission, the original signal is completely spread in a wide range of frequencies. Hence, it protects the spectrum to create nulls at of the carrier frequencies. Therefore, only a few subcarriers are usually lost, instead of the whole signal [26, 27, 34, 35, 63].

In this study, three frequency selective channels, (Indoor, ITU-R Vehicular A, and SUI-1) are tested to see the effects of practical wireless multipath channels. The characteristics of each channel model are as follows:

- **Indoor channel model:**

The Indoor channel model is considered as an empirical channel model. In case of realistic indoor channel model, it utilizes the following characteristics [76]:

- 16 taps
- RMS delay spread= 80 ns
- Bandwidth= 20 MHz

- **ITU-R vehicular A channel model**

An ITU-R channel model [16] is also an empirical channel model. Generally, ITU-R has three different type of test environment:

1) Indoor office
2) Outdoor to indoor pedestrian
3) Vehicular (high antenna)

ITU-R vehicular channel model with a high antenna has been used in this study.

This channel model has variation in its delay spread dramatically, this is the reason it contains two different delay spreads in case of each environment for a test, which are:

1) Low delay spread (channel A)
2) Medium delay spread (channel B)

ITU channel model A for vehicular test environment is used in simulations and consists of following specifications:

- 6 taps
- Max delay spread= 2.5 μs
- Bandwidth= 20 MHz

- **SUI-1 channel model**:

Stanford university interim (SUI) channel has six types of channel models naming as SUI-1, SUI-2, SUI-3, SUI-4, SUI-5, SUI-6. SUI-1 has been used in this study.

The reason for classifying these models into different type is that every model has different Doppler spreads, delay spread, line-of-sight (LOS) or non-line-of-site (non LOS) properties, and three terrain types are present in these six models.

Characteristics of SUI-1 channel are as follows:

- Terrain type: C
- Doppler Spread: low
- delay spread: low
- LOS: high

There are three kinds of taps for this channel model tap 1, tap 2, tap 3. It comprises the following specifications that have been considered in this study [48]:

- Rician fading channel
- Delay spread =0.9 µs (clearly less frequency selective than Indoor and ITU-R channels)
- Doppler spread: 0.5 Hz
- Bandwidth= 20 MHz

Channel A has been used for medium in calculations of this study. Hence, the other specifications of this channel model are as follows [48]:

- Average power (dB): -20.0
- Percentage Occurrence P (%): 40 %
- Associated RMS Delay Spread: 370 (ns)

Noise variance uncertainty:

As PU signal is detected under different SNR values, there is a limit for reaching reliable sensing of the PU signal. Below a certain level, a PU cannot be detected. This level is known as the threshold value λ. To calculate λ, it depends on the PU noise variance in ED based SS methods. Hence, it becomes obligatory to consider the effects of noise variance uncertainty. As NU changes, the value for λ also needs to change to reach $P_{FA} = 0.1$. Interference to PU signal may also occur, which can also degrade the performance for the detection of the signal. Fading, shadowing and non-line of sight, etc. can be the reason for interferences to PU signal. Thus, the noise and interference power level may change over time.

There are two types of noise variance interference which can arise due to following facts:

1) Receiver device uncertainty,
2) Environmental noise variance uncertainty.

The receiver components have non-ideal behavior. So noise variance uncertainty can arise due to this nonidelity in the receiver components, especially on the analog RF side.

Another reason is that thermal noise of these components has time-varying property. So this time variation in thermal noise also becomes the reason for noise variance uncertainties in receiver devices.

Regarding the environment, the main reason for occurrence of noise (interference) variance uncertainty is that sometimes other users start operating on the same frequency band. Other users occasionally start transmission unintentionally but sometimes they do it with their intention. Also strong transmission in adjacent frequency channels usually leak interference power to the frequency channel under sensing. Hence, in such scenarios, the power of the noise + interference level changes, which cause uncertainty in noise variance.

Any detector suffers from uncertainties caused by the device. But, foremost reason for noise power uncertainty in a CR network is the possible interference from different transmissions when other opportunistic devices, e.g., SU devices start transmitting in the same frequency band of the PU signal. In most of the studies on NU, only the uncertainty of the additive white Gaussian noise level is considered, and this is the model also in our study. The statistical properties of other interference sources are quite different, and depending also on the SS method, the AWGN model might not be applicable to them.

Different types of NU have been considered in this study when calculating the results using proposed FD-AC based method and traditional ED method under AWGN as well as under frequency selective channel cases. There are four cases for noise power that has been taken into account.

- **4 cases of NU:**
- **NU case 1:**

In the first case, P_D is estimated by both detectors under different SNR cases without the presence of noise variance uncertainty.

- **NU case 2:**

0.1 dB value has been used for small noise power uncertainty.

- **NU case 3:**

In order to view the intermediate noise power uncertainty, 0.5 dB value has been used.

- **NU case 4:**

For large noise variance uncertainty, 1 dB value has been considered in order to see the performance of each detector in huge practical challenges.

5. NUMERICAL RESULTS AND ANALYSIS OF COMPUTATIONAL COMPLEXITY

In this chapter, we analyze the performance of the proposed FD-AC method with the presence and absence of the CSS element. The performance results are compared with those of the traditional ED. NU and different channel characteristics are considered for both detectors in their processing. OFDM with a known time lag is also considered and its results are compared with the results obtained with the algorithm that does not assume knowledge of the time lag.

The target P_{FA} is set to 0.1 in all simulation cases. The time record length is 102400 complex samples with 1000 Monte Carlo simulation instances applied for reliable evaluation of the detection probability. These tests are carried out with the same SNR range of -30 dB to 5 dB with 1 dB step size. Matlab is used as the simulation tool in this study.

The results for the FD-AC method are obtained in the four cases of noise uncertainty that were mentioned in Chapter 4, and the results are compared with traditional ED under different SNR values in order to sense the availability of PU signal.

In ED, the noise variance should be a known parameter while calculating the detection performance. But this prior information of noise power is always uncertain in real cases and the receiver has to estimate this value. The threshold is calculated to reach the target false alarm probability for the worst case of the noise uncertainty range, which degrades the detection performance in the presence of a PU. Therefore, it becomes very difficult to distinguish a very weak PU signal from noise [43]. This can also be seen in the following figures. After setting experimental threshold values, the performances of different detectors are compared with each other.

Simulations for detecting PU signal has been carried out in two scenarios which are:

1) Under AWGN channel,
2) Under the frequency selective channel.

5.1 Calculations under AWGN channel

Different scenarios have been taken into account under AWGN channel to detect PU signal by FD-AC and ED methods which are as follows.

5.1.1 FD-AC based SS technique with a known OFDM signal parameters under AWGN channel

When the signal characteristics are known, the test-statistics are calculated by using a known time lag of the correlation peak. Two situations are taken into account:

- Calculating FD-AC based detector with/without CSS under various noise variance uncertainty cases which have been mentioned in Chapter 4.

➢ **NU case 1 vs. NU case 2:**

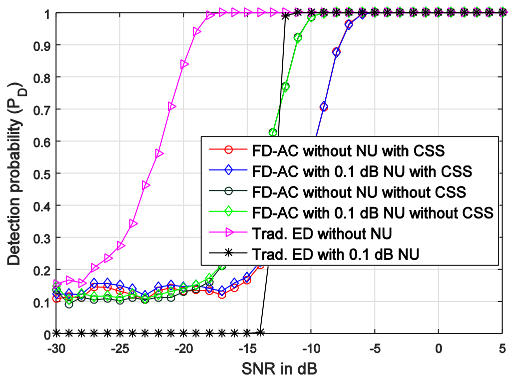

Figure 5.1. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 0.1 dB NU and without/with compressed spectrum sensing under AWGN.*

➢ **NU case 1 vs. NU case 3:**

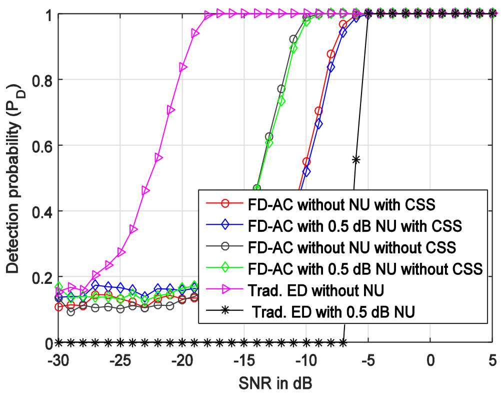

Figure 5.2. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 0.5 dB NU and without/with compressed spectrum sensing under AWGN.*

➢ **NU case 1 vs. NU case 4:**

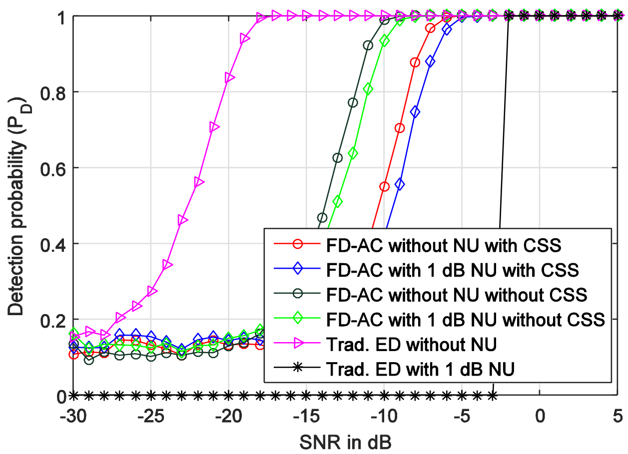

Figure 5.3. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 1 dB NU and without/with compressed spectrum sensing under AWGN.*

Figure 5.1, Figure 5.2, and Figure 5.3 show the detection performance of a CP-OFDM signal with known signal parameters, which acts as PU signal, under different SNR values using simulations in Matlab, when FD-AC based method and ED are carried out for processing under AWGN channel and under different NU cases.

5.1.2 FD-AC based SS technique with an unknown OFDM signal parameters under AWGN channel

Let us consider the unknown time lag cases now, when prior information of the OFDM signal parameters is not available. In this situation all other procedures for sensing the PU signal remains the same, but the only difference is that the algorithm does not use the known time lag of $N_d + 1$. Instead, it uses the second maximum correlation peak value as the test-statistic. As the maximum correlation peak generally appears with a zero lag, the second highest amplitude peak is expected to denote the CP correlation. In such circumstances, the PU detection performance is also tested in the four cases of NU.

➢ **NU case 1 vs. NU case 2:**

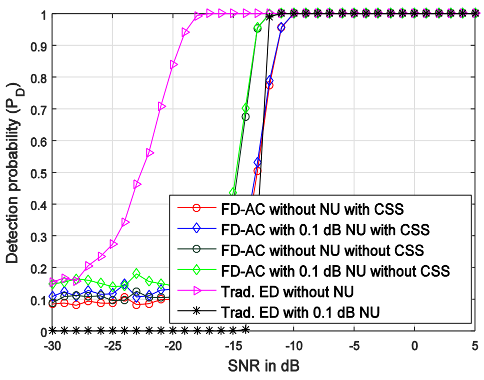

Figure 5.4. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 0.1 dB NU and without/with compressed spectrum sensing under AWGN.*

➢ **NU case 1 vs. NU case 3:**

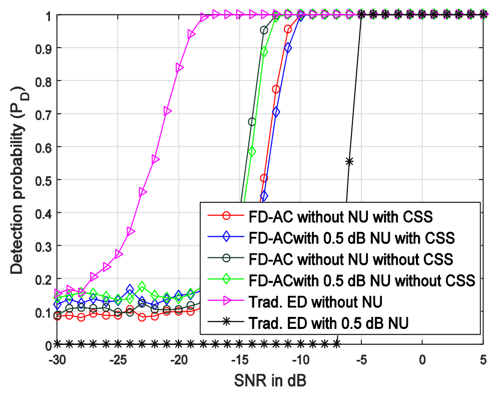

Figure 5.5. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 0.5 dB NU and without/with compressed spectrum sensing under AWGN.*

➢ **NU case 1 vs. NU case 4:**

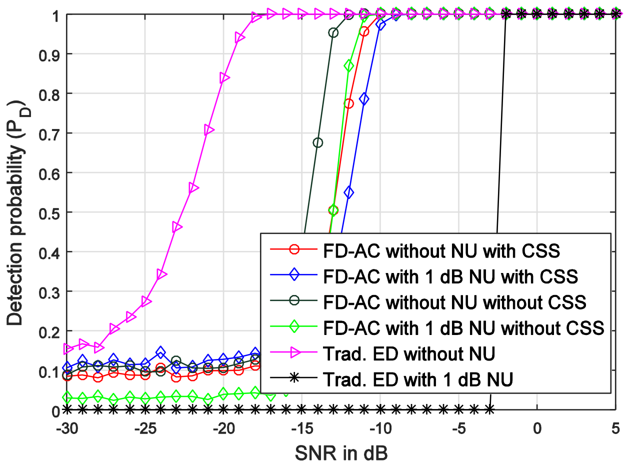

Figure 5.6. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 1 dB NU and without/with compressed spectrum sensing under AWGN.*

Figure 5.4, Figure 5.5, and Figure 5.6 show the detection performance of a CP-OFDM signal with unknown signal parameters, which acts as PU signal, under different SNR values using simulations in Matlab, when FD-AC based method and ED are carried out for processing under AWGN channel and under different NU cases.

5.2 Calculations under frequency selective channel

As it has been mentioned in Chapter 4, three frequency selective multipath channel models have been used in this study.

5.2.1 Test results under Indoor channel model

Under Indoor channel, two types of tests have been carried out which are as follows.

5.2.1.1 Test results with a known OFDM signal parameters under Indoor channel model

Detection performances of FD-AC and ED methods for CP-OFDM type PU signal are evaluated here under various SNR values using the Indoor channel model and a known OFDM signal model. The characteristics of the Indoor channel model used in this study have been described in Chapter 4.

Tests were carried out to estimate P_D under this channel and the results for the four NU cases with/without using CSS element are shown below.

- **NU case 1 vs. NU case 2:**

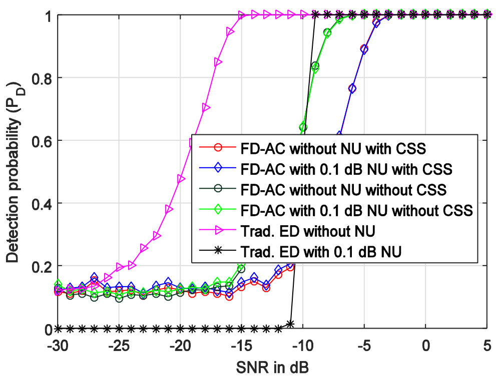

Figure 5.7. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 0.1 dB NU and without/with compressed spectrum sensing under Indoor channel.*

- **NU case 1 vs. NU case 3:**

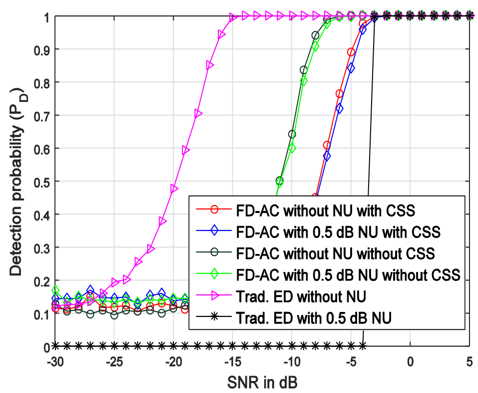

Figure 5.8. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 0.5 dB NU and without/with compressed spectrum sensing under Indoor channel.*

➢ **NU case 1 vs. NU case 4:**

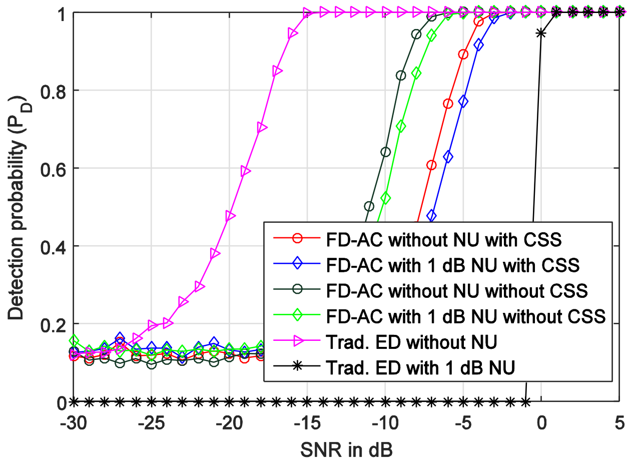

Figure 5.9. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 1 dB NU and without/with compressed spectrum sensing under Indoor channel.*

Figure 5.7, Figure 5.8, and Figure 5.9 show the detection performance of a CP-OFDM signal with known signal parameters, which acts as PU signal, under different SNR values using simulations in Matlab, when FD-AC based method and ED are carried out for processing under Indoor channel model and under different NU cases.

5.2.1.2 Test results with an unknown OFDM signal parameters under Indoor channel model

Here the results are given with the Indoor channel model for the FD-AC algorithm which doesn't assume knowledge of the OFDM useful symbol duration in the same cases as earlier.

- **NU case 1 vs. NU case 2:**

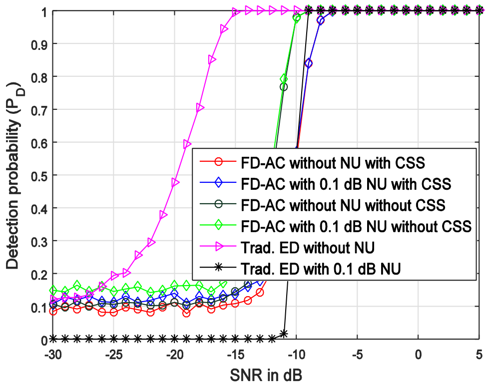

Figure 5.10. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 0.1 dB NU and without/with compressed spectrum sensing under Indoor channel.*

- **NU case 1 vs. NU case 3:**

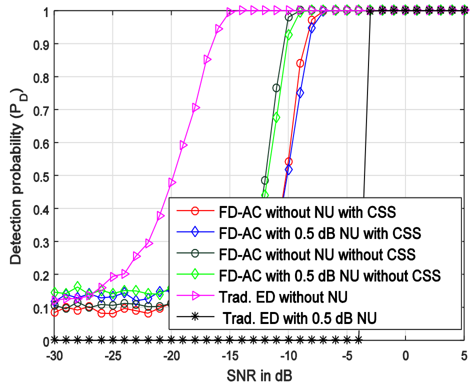

Figure 5.11. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 0.5 dB NU and without/with compressed spectrum sensing under Indoor channel.*

- **1 vs. NU case 4:**

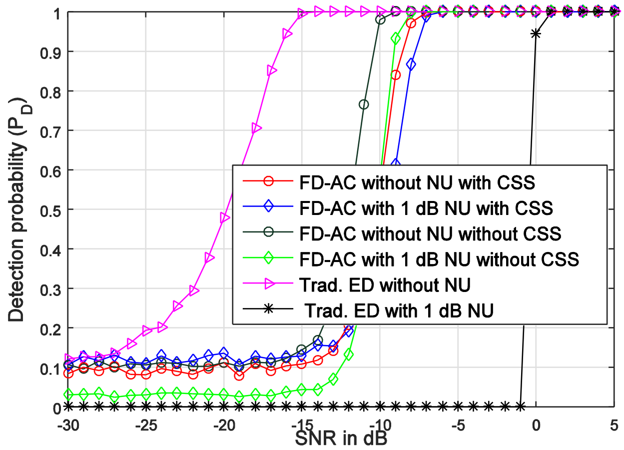

Figure 5.12. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 1 dB NU and without/with compressed spectrum sensing under Indoor channel.*

Figure 5.10, Figure 5.11, and Figure 5.12 show the detection performance of a CP-OFDM signal with unknown signal parameters, which acts as the PU signal, under different SNR values using simulations in Matlab, when FD-AC based method and ED are carried out for processing under Indoor channel model and under different NU cases.

5.2.2 Test results under ITU-R vehicular A channel model

Under ITU-R Vehicular-A channel model, two types of tests have been carried out which are as follows:

5.2.2.1 Test results with a known OFDM signal parameters under ITU-R vehicular A channel model

The sensing performances of FD-AC and ED methods have also been evaluated in the presence of the ITU-R Vehicular A channel model. Characteristics of this channel model have been mentioned in Chapter 4. The results under different NU cases when CP-OFDM has been considered as the PU signal, are as follows:

- **NU case 1 vs. NU case 2:**

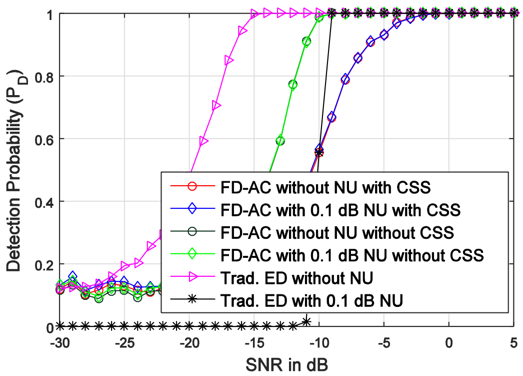

Figure 5.13. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 0.1 dB NU and without/with compressed spectrum sensing under ITU-R vehicular A channel.*

- **NU case 1 vs. NU case 3:**

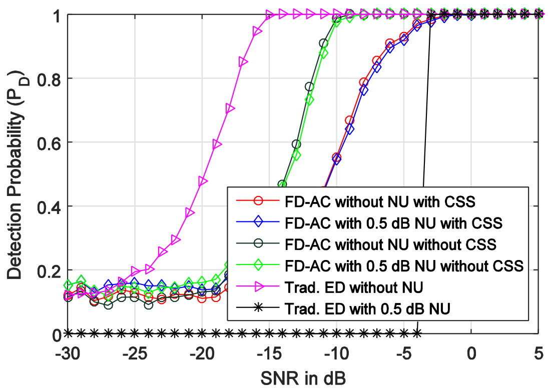

Figure 5.14. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 0.5 dB NU and without/with compressed spectrum sensing under ITU-R vehicular A channel.*

NU case 1 vs. NU case 4:

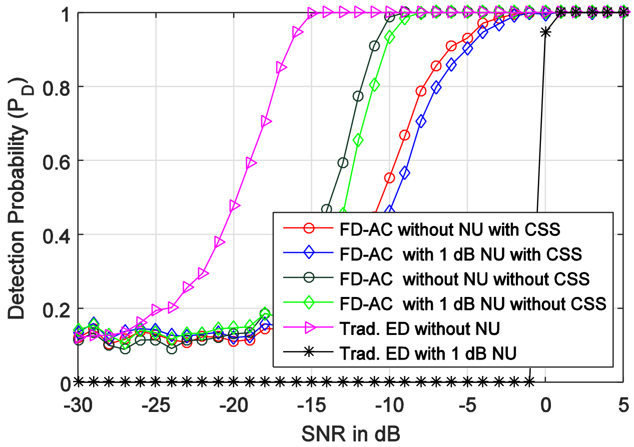

Figure 5.15. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 1 dB NU and without/with compressed spectrum sensing under ITU-R vehicular A channel.*

Figure 5.13, Figure 5.14, and Figure 5.15 show the detection performance of a CP-OFDM signal with known signal parameters acting as PU signal, under different SNR values using simulations in Matlab, when FD-AC based method and ED are carried out for processing under ITU-R vehicular A channel model and under different NU cases.

5.2.2.2 Test results with an unknown OFDM signal parameters under ITU-R vehicular A channel model

Here the results are given with the Vehicular-A channel model for the FD-AC algorithm which doesn't assume knowledge of the OFDM useful symbol duration in the same cases as earlier.

➢ **NU case 1 vs. NU case 2:**

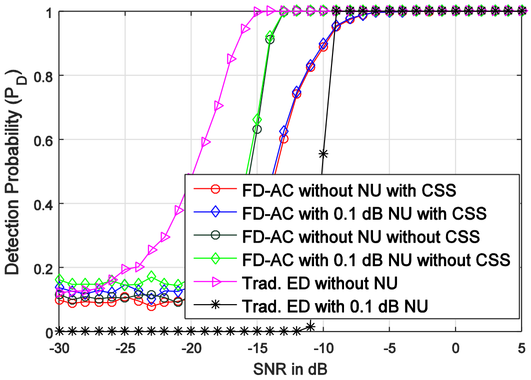

Figure 5.16. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 0.1 dB NU and without/with compressed spectrum sensing under ITU-R vehicular A channel.*

➢ **NU case 1 vs. NU case 3:**

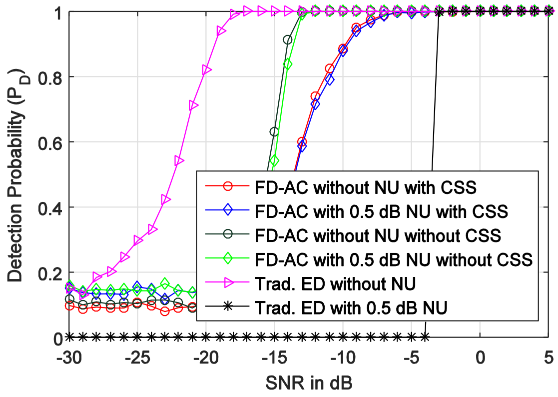

Figure 5.17. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 0.5 dB NU and without/with compressed spectrum sensing under ITU-R vehicular A channel.*

➢ **NU case 1 vs. NU case 4:**

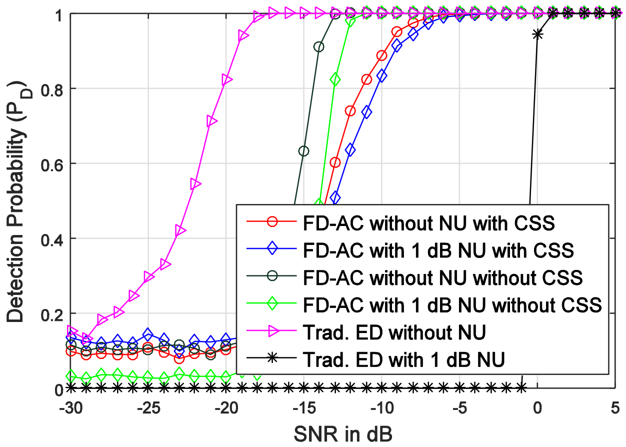

Figure 5.18. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 1 dB NU and without/with compressed spectrum sensing under ITU-R vehicular A channel.*

Figure 5.16, Figure 5.17, and Figure 5.18 show the detection performance of the a CP-OFDM signal with unknown signal parameters, which acts as PU signal, under different SNR values using simulations in Matlab, when FD-AC based method and ED are carried out for processing under ITU-R vehicular A channel model and under different NU cases.

5.2.3 Test results under SUI-1 channel model

Under SUI-1 channel model, two types of tests have been carried out which are as follows.

5.2.3.1 Test results with a known OFDM signal parameters under SUI-1 channel model

SUI -1 channel has also been applied to evaluate the detection performance of PU by FD-AC based method and ED. Its channel characteristics have been mentioned in Chapter 4. The results with this channel under different NU cases are as follows:

- **NU case 1 vs. NU case 2:**

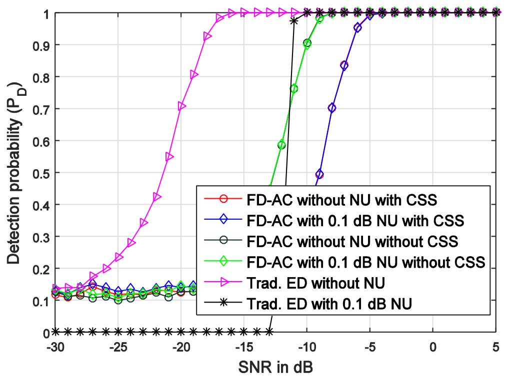

Figure 5.19. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 0.1 dB NU and without/with compressed spectrum sensing under SUI-1 channel.*

- **NU case 1 vs. NU case 3:**

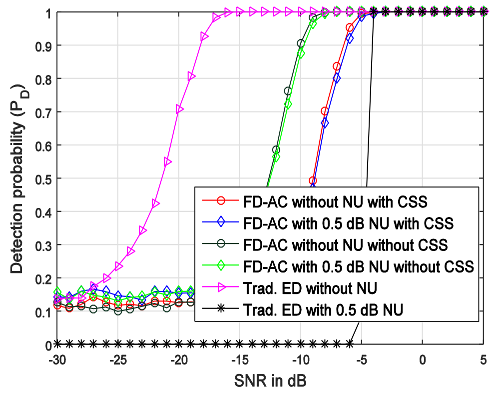

Figure 5.20. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 0.5 dB NU and without/with compressed spectrum sensing under SUI-1 channel.*

- **NU case 1 vs. NU case 4:**

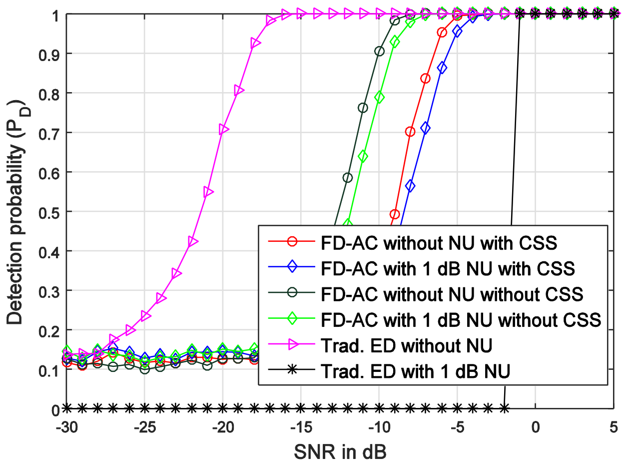

Figure 5.21. *Detection probability of traditional ED and proposed FD-AC in the case of a known time lag without/with 1 dB NU and without/with compressed spectrum sensing under SUI-1 channel.*

Figure 5.19, Figure 5.20, and Figure 5.21 show the detection performance of a CP-OFDM signal with known signal parameters which acts as PU signal, under different SNR values using simulations in Matlab, when FD-AC based method and ED are carried out for processing under SUI-1 channel model and under different NU cases.

5.2.3.2 Test results with an unknown OFDM signal parameters under SUI-1 channel model

In a case when signal characteristics are not known, hence, in such situation the results with this channel under four NU cases are as follows.

- **NU case 1 vs. NU case 2:**

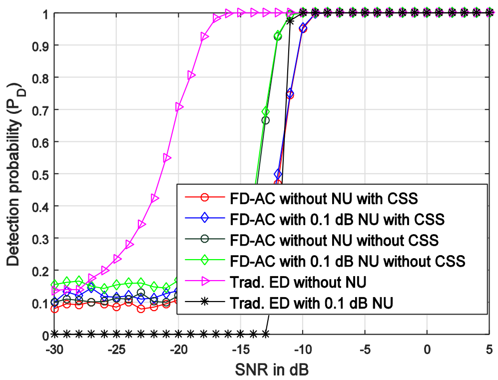

Figure 5.22. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 0.1 dB NU and without/with compressed spectrum sensing under SUI-1 channel.*

- **NU case 1 vs. NU case 3:**

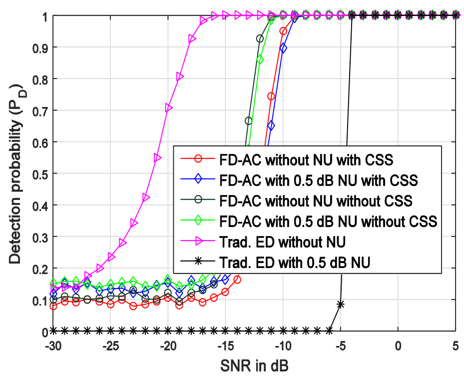

Figure 5.23. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 0.5 dB NU and without/with compressed spectrum sensing under SUI-1 channel.*

➢ **NU case 1 vs. NU case 4:**

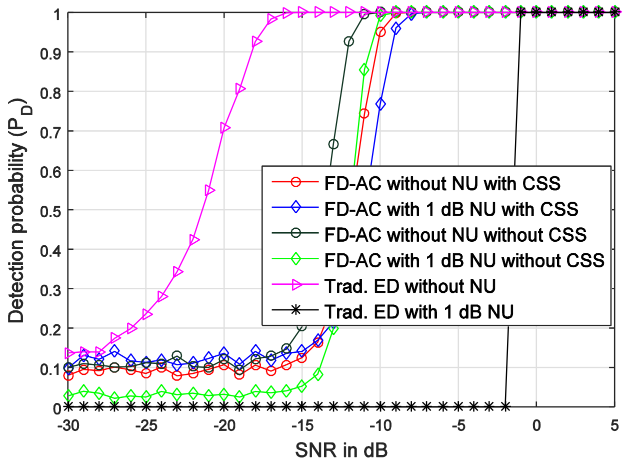

Figure 5.24. *Detection probability of traditional ED and proposed FD-AC in the case of an unknown time lag without/with 1 dB NU and without/with compressed spectrum sensing under SUI-1 channel.*

Figure 5.22, Figure 5.23, and Figure 5.24 show the detection performance of a CP-OFDM signal with unknown signal parameters acting as PU signal, under different SNR values using simulations in Matlab, when FD-AC based method and ED are carried out for processing under SUI-1 channel model and under different NU cases.

5.3 Discussion of the tests

The above test figures demonstrate the detection performance of the FD-AC algorithms with known time lag and unknown time lag, respectively, against the traditional ED as the reference sensing method. These results were given both with and without the compressed sensing element.

The results were given for 0 dB and 0.1 dB noise uncertainties to observe the performance of FD-AC method versus ED under very low noise variance uncertainties. Under 0.1 dB NU, the performances of the two detectors are rather similar, there is no clear difference under such low NU conditions.

The results were also given for 0.5 dB and 1 dB noise uncertainties, and the robustness of FD-AC methods can be clearly observed.

Another important observation is that the unknown lag model has clearly better sensitivity. The reason for this is as follows.

Due to channel effects and noise, it may happen that the AC peak is not precisely at the expected location. Even in the known lag case, there is a need to search for the peak in the neighborhood of the expected lag, within a few high-rate sample intervals. The performance vs. complexity tradeoffs related to this idea remains a topic for future studies.

The corresponding results were presented also for three different frequency selective channel models, in the same configurations as in the AWGN case. Under highly frequency selective channels, both FD-AC with and without the compressed sensing element exhibit robustness against noise uncertainty and under real-life channel characteristics. Also in these studies, the algorithm which searches for the maximum correlation peak with non-zero lag systematically outperformed the algorithm which uses the autocorrelation at the expected lag value only.

5.4 Computational complexity

The computational complexities of the SS algorithms are calculated in terms of the number of real multiplications that the methods must perform to complete the decision statistics. The FD-AC methods need $\left(M+m_{\Delta}\right)K$ samples for M correlations, and the same sample complexity is assumed for the other methods included in the comparison. The comparison includes also, as a reference, an eigenvalue based method, which is well-known as a SS method which is robust to NU [25, 70]. Table 5-1 shows generic expressions, as well as numerical values in our example case [28].

Table 5-1. *Computational complexity of traditional and proposed SS algorithms.*

SS algorithm	**Complexity** (Real multiplications)	**Numerical value for our scenario**
Basic ED	$2N$	204800
Eigenvalue detector	$4MLN+O\left(M^3L^3\right)$	3277313
Time domain AC based detector	$6N$	614400
Proposed FD-AC CSS with unknown time lag	$\left(M+m_{\Delta}+1\right)K\left(\log_2\left(K\right)-3\right)+2MK_{comp}$	772368

(Notes: Complex multiplication assumed to take 4 real multiplications. Squared magnitude takes 2 real multiplications. Split radix algorithm used for FFT.)

In our example case, it is assumed that $m_{\Delta} = 0$, in which case the FD-AC is obtained from the squared magnitudes of the subband samples. The number of used subbands with/without CSS is $K_{comp} = 242$ or $K_{comp} = 1024$, respectively. The eigenvalue detector is based on maximum eigenvalue over minimum eigenvalue, and it uses the smoothing factor of $L = 8$ and an overlapping factor of $M_{over} = 1$. The used smoothing and overlap factors result in relatively low complexity, which slightly compromises the performance of SS. For instance, when the number of samples is 102400, the overall computational complexity (number of real multiplications) of the eigenvalue based algorithm is 3277313, contrary to the 614400 and 772368 counterparts to the time-domain AC and proposed FD-AC based SS methods, respectively. The proposed FD-AC based SS method has somewhat higher complexity than the basic time-domain AC method, but the complexities of both methods are significantly smaller than those of the eigenvalue based techniques. In time domain implementation, it is enough to do the autocorrelation calculation over the CP length only, if the SS device is synchronized to the PU signal. This would reduce the complexity and reduce the noise in the decision for test-statistic. But such assumption is not realistic in practical SS scenarios.

6. CONCLUSION AND FUTURE WORK

In this chapter, the major contributions of the work are concluded briefly. In this study, we have considered a novel SS technique in CR environment, in order to overcome some essential real-life problems. Basics of CR and different SS algorithms were discussed briefly at the beginning of this thesis. Then FFT and IFFT algorithms were described as well, as these processes are utilized by our proposed SS method. Frequency domain autocorrelation based SS method was exploited in this study to fight the challenges that SS algorithms are facing. The proposed method was explained in details in this thesis and then its sensing performance was tested in Chapter 5.

Several challenges were addressed in the first chapters of this study and their effective solutions were demonstrated by the performance results of our detector. Noise uncertainty, frequency selective channels, and computational complexity are crucial issues, which could be handled in an improved manner by the proposed sensing algorithm. It was observed in our results, that the proposed detector is capable of overcoming the problem of noise uncertainty and it is efficient enough to differentiate between the signal and noise in the low SNR regime. It has been shown that detection performance of the proposed FD-AC based detector is better than traditional ED under both moderate and high noise uncertainty values. It has also been shown that the FD-AC based method is rather insensitive to the effects of frequency selective channels. This was tested with the Indoor, ITU-R Vehicular-A, and SUI-1 channel models.

The eigenvalue based detector, besides performing well with noise uncertainty issues, is still not a good option to utilize for SS, as it has high computational complexity. Autocorrelation based SS method has been explored regarding this issue and it was found out that it has much smaller complexity than the eigenvalue based detector. Autocorrelation in the frequency domain has slightly higher complexity than the corresponding time domain algorithm. On the other hand, due to its ability to facilitate partial band sensing (CSS), this method is better suited to real life sensing scenarios, where a wideband PU channel is partly interfered by strong narrowband PU or SU transmissions. It was also observed that utilizing the knowledge of the time lag of the correlation peak doesn't bring significant benefit to the sensing performance, and thus the knowledge of the CP-OFDM parameters is not essential to the sensing performance.

CP-autocorrelation based sensing methods are applicable only for CP-OFDM type primaries, but OFDM is a very popular waveform in recent wireless communication system development. Hence CP-autocorrelation based sensing methods find important applications for wideband sensing, e.g., in the context of TV white-space CR and ISM (WLAN) frequency bands. The proposed detector has great flexibility for wideband multimode, multichannel SS of PU signals, possibly with different bandwidths, FFT sizes, and CP lengths while utilizing CP-OFDM as PU waveform. FD-AC is also applicable to cases where OFDM signals are partly overlapped with other secondary transmissions or other interfering PU transmissions. Furthermore, the proposed methods can be fully combined with subband energy detection based wideband/multichannel SS approaches [27, 33]. A wideband sensing platform could run different sensing processes in parallel for different frequency channels and different types of primaries.

In the future work, in order to complete the current investigations, it is important to quantify analytically and experimentally the performance of FD-AC based sensing in different configurations. Especially, analytical derivation of the sensing threshold is an important task to be completed. Also more extensive comparisons need to be carried out, including cases where the sensing utilizes only a relatively small part of the active OFDM subcarriers, as well as frequency-interleaved sensing scenarios.

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